OPEN ACCESS

TẠP CHÍ SINH LÝ HỌC VIỆT NAM ISSN 1859 - 2376

REVIEW ARTICLE | Received 02.10.2026 | Revised 02.11.2026 | Accepted 03.11.2026 | Published online 06.11.2026

HEART RATE VARIABILITY IN THE ASSESSMENT OF CARDIAC AUTONOMIC FUNCTION IN TYPE 2 DIABETES: FROM TIME AND FREQUENCY DOMAINS TO NONLINEAR ANALYSIS

Ngoc Hien Tran[1], Trong Nhan Le[2], Linh Ly Luong[2], Hong Tam Nhan[2], Quoc Tuan Le[1*]

[1]University of Medicine and Pharmacy at Ho Chi Minh City

[2]Hong Bang International University

*** Corresponding Author:**
Quoc Tuan Le,
University of Medicine and Pharmacy at Ho Chi Minh City
Corresponding Author e-mail:
dr.lequoctuan@ump.edu.vn

Copyrights: © 2026 Ngoc Hien Tran et al. This is an open-access article distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License (CC BY-NC-SA 4.0), which permits non-commercial use, distribution, and reproduction, provided that appropriate credit is given to the original author(s) and source of the work.

ABSTRACT

Cardiac autonomic neuropathy (CAN) is a common complication of type 2 diabetes. It is often underdiagnosed until it presents with cardiovascular complications such as silent myocardial ischaemia, orthostatic hypotension or arrhythmia. Cardiovascular autonomic reflex tests (CARTs) remain the diagnostic reference, but they need time, trained staff and good patient cooperation, which limits their use in busy clinics. Analysis of heart rate variability (HRV) from a five-minute resting recording is quick, non-invasive and inexpensive. This narrative review analyses HRV across three domains: time, frequency and nonlinear. For each domain, we explain the physiological basis of the main indices and their limits. We discuss the position of HRV relative to CARTs, summarise studies of its clinical use and its prognostic value in type 2 diabetes, and propose a standard recording protocol and a minimum reporting checklist. Based on current evidence, we suggest that HRV may be most useful for screening and follow-up, while the diagnosis of CAN still relies on CARTs; this framework has not yet been validated. Time- and frequency-domain indices measure the amplitude of heart rate fluctuations, whereas nonlinear indices, such as sample entropy and the short-term scaling exponent of detrended fluctuation analysis (DFA-α1), describe how these fluctuations are organised. We hypothesise that nonlinear indices may retain some discriminating ability in advanced disease, when amplitude-based indices cluster near the lower limit of their range, but this has not been tested directly. Validated cut-offs are lacking for most indices, and no reference values exist for the Vietnamese population. Therefore, standard recording and complete reporting are essential if HRV is to become a reliable clinical tool.

Key words: heart rate variability, cardiac autonomic neuropathy, type 2 diabetes.

Citation: Ngoc Hien Tran et al. Heart rate variability in the assessment of cardiac autonomic function in type 2 diabetes: From time and frequency domains to nonlinear analysis. *Vietnam Journal of Physiology*. 2026; 30(4):01-12. doi:10.54928/vjop.v30i4.674.

1. Introduction

The autonomic nervous system (ANS) adjusts heart rate beat by beat. When this regulation is impaired, the clinical consequences are diverse and usually appear late. They include resting tachycardia, exercise intolerance, orthostatic hypotension, silent myocardial ischaemia, arrhythmia and sudden cardiac death [1, 2]. In type 2 diabetes, cardiac autonomic neuropathy (CAN) affects about one in five patients. Its prevalence rises to around 65% with age and disease duration, and estimates depend on the diagnostic criteria used [3, 4]. Autonomic dysfunction is also present in prediabetes and the metabolic syndrome [5, 6]. Therefore, the group at risk is wider than patients with established diabetes.

Early detection also has prognostic relevance. CAN is linked with silent myocardial ischaemia, arrhythmia and higher cardiovascular and all-cause mortality [1, 2]. Low heart rate variability (HRV) also predicts cardiovascular events in people with type 2 diabetes who appear to be at low risk by conventional factors [7]. Autonomic imbalance has also been linked with haemodynamic instability and complications around surgery [8]. The topic is therefore relevant to cardiology and anaesthesia as well as endocrinology.

The diagnosis of CAN is based on cardiovascular autonomic reflex tests (CARTs), often called the Ewing battery [3]. These tests are specific, but they are less sensitive in early disease. They require trained staff, blood pressure monitoring and good patient cooperation. The Valsalva manoeuvre also needs caution in proliferative retinopathy [3, 9]. In a crowded outpatient clinic, routine CARTs are rarely feasible.

HRV analysis offers another approach. A five-minute resting electrocardiogram (ECG) is simple, non-invasive and inexpensive. It asks little of the patient and can be processed with standard software [10, 11]. However, HRV is easy to misuse. There are many indices and the names are confusing. The physiological meaning of some indices is still debated, and recording conditions affect the result more than many users expect [12, 13].

Published HRV studies from Vietnam have used time- and frequency-domain indices [14-16]. In our search, we did not identify a full-length Vietnamese study that reported nonlinear HRV indices, such as entropy and fractal measures. Nonlinear indices are also under-reported internationally. A recent meta-analysis in the metabolic syndrome could not pool them because too few studies reported them [6]. This review has four aims. First, we explain the physiological basis of the main HRV indices in the three domains. Second, we summarise standard recording conditions, common technical errors and a minimum reporting checklist. Third, we discuss the possible position of HRV relative to CARTs and summarise studies of its clinical use. Fourth, we review the evidence on prognosis and the limits that should be stated when results are interpreted.

1.1. Literature search

This is a narrative review. We searched PubMed/MEDLINE and Google Scholar for articles published from January 1990 to 30 June 2026, and the search was updated in October 2026 during revision. Search terms included “heart rate variability”, “cardiac autonomic neuropathy”, “nonlinear analysis”, “entropy” and “detrended fluctuation analysis”. These were combined with “type 2 diabetes”, “prediabetes” and “cardiovascular risk”. Vietnamese studies were searched in Google Scholar and in Vietnamese medical journals with online archives. We also checked the reference lists of key reviews and guidelines. We included articles in English or Vietnamese that addressed HRV methods, the diagnosis of CAN, or the clinical or prognostic use of HRV in prediabetes or diabetes. Consensus statements, guidelines, meta-analyses and original methodological papers were given priority regardless of publication date. Among other studies, priority was given to those published in the last five years. Because this is a narrative review, we did not perform a formal risk-of-bias assessment or pool results. When we state that a type of study is lacking, this means that our search did not identify one.

1.2. Scope of the review

Commercial HRV software reports dozens of parameters for each recording. Many of them are descriptive statistics, the same quantity in different units, or indices that are closely related mathematically. The number of truly independent pieces of information is much smaller. Reporting all of them adds noise rather than value. We therefore limited this review to indices that meet three conditions. They have a clear physiological basis. They appear in guidelines or are widely used, so studies can be compared. They can be computed

reliably from a five-minute resting recording, which is the most practical length in a clinic.

Several groups fall outside this scope. Geometric indices, such as the HRV triangular index and the triangular interpolation of the NN interval histogram (TINN), need long recordings. Very-low-frequency (VLF) and ultra-low-frequency (ULF) power have cycle lengths longer than a short recording, and their physiological origin is uncertain. The long-term scaling exponent of detrended fluctuation analysis (DFA-α2) needs far more beats than five minutes provide. Multiscale entropy and newer entropy variants are promising, but clinical data are limited and their parameters are not standardised. Chaos-based measures, such as Lyapunov exponents, correlation dimension and recurrence quantification, are very sensitive to noise and series length. Deceleration capacity and heart rate turbulence need Holter recordings and belong mainly to post-infarction risk assessment. Leaving these indices out reflects the current state of evidence, not a judgement on their potential.

2. Physiological basis of heart rate variability

2.1. What HRV measures

HRV is the variation in time between consecutive heartbeats over a given recording period. It is measured on the NN series, which is the RR series after removal of non-sinus beats [10, 11]. HRV does not measure heart rate itself, but how much it changes. Two patients with the same heart rate of 78 beats/min can have very different HRV, and this difference reflects the capacity of autonomic control. In general, reduced variability indicates impaired autonomic regulation rather than greater stability.

2.2. Why vagal effects are fast and sympathetic effects are slow

The two autonomic branches act on the sinoatrial node at very different speeds. This difference underlies the interpretation of most HRV indices.

Anatomy provides part of the background. Parasympathetic ganglia lie in or very close to the wall of the target organ, so vagal postganglionic fibres are very short. Sympathetic ganglia lie in the paravertebral chain, so sympathetic postganglionic fibres are much longer. Preganglionic fibres are thinly myelinated type B fibres, while postganglionic fibres are unmyelinated type C fibres that conduct at about 0.5 to 2 m/s. The longer sympathetic pathway therefore adds some delay. However, an extra 10 cm or so of type C fibre adds only about 0.1 s. This cannot explain a sympathetic delay of several seconds.

The main reason is receptor signalling. Acetylcholine released from vagal endings binds M2 muscarinic receptors. The βγ subunits of the activated G protein then open acetylcholine-activated G protein-gated inwardly rectifying potassium (GIRK) channels directly, without a second messenger. Acetylcholinesterase breaks down acetylcholine within milliseconds. As a result, vagal effects on heart rate begin and end within about one second [11, 12].

Sympathetic control is slower. Norepinephrine acts on β1-adrenergic receptors and works through adenylyl cyclase and cyclic adenosine monophosphate (cAMP). cAMP then modulates pacemaker channels and protein kinase A targets. The effect takes several seconds to develop. It also fades slowly, because norepinephrine is removed mainly by reuptake and diffusion rather than by rapid enzymatic breakdown [11, 12].

As a result, only vagal modulation is fast enough to change heart rate within a single breath. This is the basis of respiratory sinus arrhythmia (RSA), and it is why indices of fast, beat-to-beat change (the root mean square of successive differences [RMSSD], high-frequency [HF] power and the short-term Poincaré spread [SD1]) are used as markers of vagal activity. Slower oscillations are linked to the baroreflex, vascular control and mental state. They fall into lower frequency bands and have mixed origins [10, 11].

2.3. Sequence of damage in diabetic CAN

In diabetes, the long vagal fibres are affected before sympathetic fibres, in keeping with length-dependent nerve damage. Early CAN therefore shows as lower RMSSD, HF power and SD1, with loss of the respiratory swing in heart rate. Resting heart rate tends to rise because vagal restraint is lost first. As the disease progresses, sympathetic fibres are also affected, and low-frequency (LF) power, the standard deviation of NN intervals (SDNN) and the long-term Poincaré spread (SD2) fall further. In advanced CAN, HRV is nearly abolished. Heart rate becomes fixed and responds little to physiological stimuli [3, 4]. The mechanisms include oxidative stress, advanced glycation end-products acting through the receptor for advanced glycation end-products (RAGE), low-grade

inflammation and ischaemia of the small vessels that supply the nerves [1, 2].

3. The three domains of HRV analysis

3.1. Time domain

Time-domain indices are calculated directly from the NN series. They are easy to understand and are the most widely used.

SDNN is the standard deviation of all NN intervals. It reflects total variability across all time scales within the recording, with input from both branches. In a five-minute recording, SDNN mainly reflects short-term variation, and it is not directly comparable with SDNN from a 24-hour recording.

RMSSD is the root mean square of successive differences between adjacent NN intervals. Because it only looks at beat-to-beat change, it mainly reflects vagal activity and is little affected by slow trends.

pNN50 is the percentage of successive NN differences greater than 50 ms. It carries the same information as RMSSD but uses a fixed threshold. In older people and in patients with very low HRV, few differences exceed 50 ms, and pNN50 is often zero [10]. We mention it mainly because it appears in most software reports and in published Vietnamese studies.

In practice, SDNN and RMSSD cover most of the time-domain information. One describes overall variability and the other describes vagal activity.

3.2. Frequency domain

Time-domain indices show how large the fluctuations are, but not how fast they are. Spectral analysis addresses this by dividing signal power into frequency bands, usually with the fast Fourier transform (FFT) or an autoregressive (AR) model [10, 11].

HF power (0.15–0.40 Hz) corresponds to oscillations at the breathing frequency. It reflects vagal activity through RSA.

LF power (0.04–0.15 Hz) reflects slower regulation, mainly the baroreflex. Both branches contribute to it, so it should not be read as a pure sympathetic marker.

VLF power (below 0.04 Hz) is influenced by thermoregulation, hormones and inflammation. Reliable VLF estimates need recordings longer than five minutes [10]. VLF is described here only for conceptual distinction and is outside the scope of this review.

Two technical points matter. First, NN intervals are not evenly spaced in time, but the FFT needs evenly sampled data. The series must therefore be interpolated before spectral analysis, usually with cubic splines. Most HRV software does this automatically. Second, absolute units (ms^2) and normalised units (n.u.) give different values and support different interpretations. The unit must always be stated [17].

The LF/HF ratio. This ratio was long used as an index of sympathovagal balance, and it still appears often in clinical reports. It does not measure that balance accurately. It is strongly affected by breathing rate, posture and acute stress, and it rests on physiological assumptions that have not been confirmed [18]. In the meta-analysis by Benichou et al., most HRV indices were lower in type 2 diabetes, but LF/HF did not differ from controls [19]. We suggest that LF/HF should not be used, or should be reported only with a clear warning about its meaning.

3.3. Nonlinear domain

Heart rate control is not a linear system. SDNN and RMSSD tell us whether fluctuations are large or small. They do not tell us how the fluctuations are organised. Nonlinear indices were developed to describe this structure [10].

3.3.1. Poincaré plot: SD1 and SD2

The Poincaré plot is a scatter plot in which each NN interval (NN_n) is placed on the horizontal axis and the next interval (NN_{n+1}) on the vertical axis. In a healthy person, the points form an elliptical cloud oriented at 45° along the line of identity (Figure 1). SD1 is the spread perpendicular to this line. It reflects beat-to-beat variation and is linked to vagal activity. SD2 is the spread along the line. It reflects longer-term variation under the combined control of both branches [10].

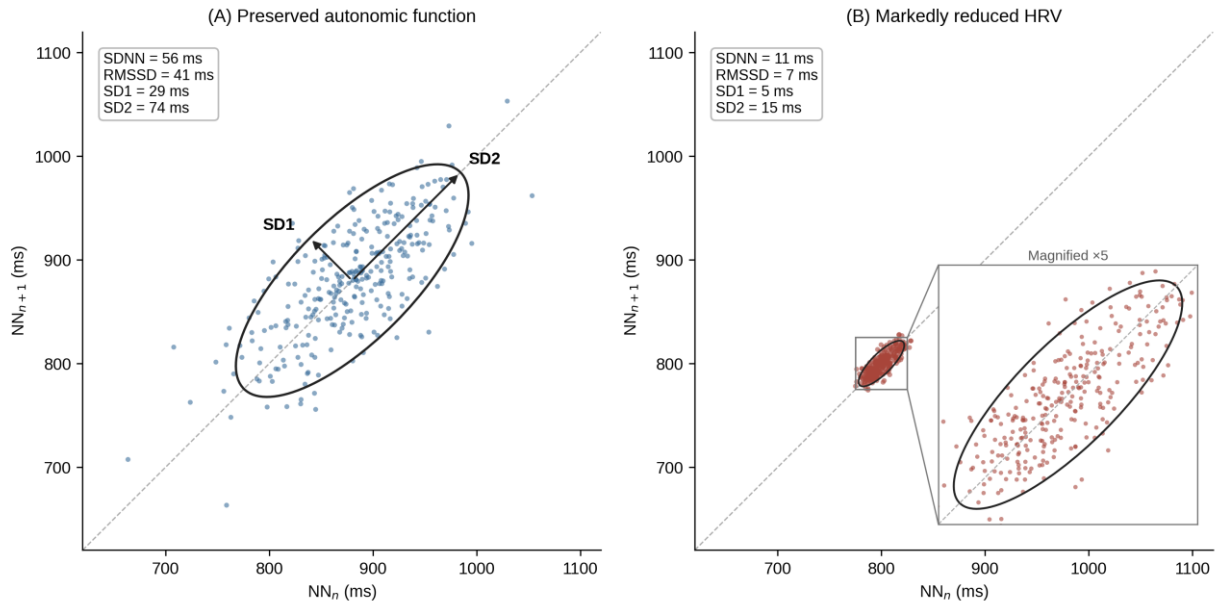


Figure 1. Poincaré plots in a person with preserved autonomic function (A) and in a patient with markedly reduced heart rate variability (B). Both panels share the same axes. The inset in panel B is magnified five times. Data are simulated for illustration (autoregressive model, about 300 beats).

The plot is a convenient way to explain HRV to non-specialists, because the cloud shrinks to a small cluster when autonomic control fails. However, SD1 and SD2 are tied mathematically to RMSSD and SDNN. SD1 equals RMSSD divided by √2, and SD2 can be derived from SDNN and SD1 [10]. Therefore, the two indices add visual insight more than independent biological information. For this reason, some authors class them as geometric rather than truly nonlinear indices.

3.3.2. Entropy: ApEn and SampEn

Entropy measures describe how predictable the NN series is from its own recent values. In a healthy person, the series is less predictable, because heart rate is continuously adjusted in response to many small inputs. When autonomic control is lost, heart rate becomes more monotonous and more predictable. Entropy expresses this degree of irregularity as a number.

Approximate entropy (ApEn) was introduced by Pincus in 1991 [20]. It estimates how often short patterns in the NN series repeat. It uses two parameters: the pattern length m, usually 2, and the tolerance r, usually 0.2 times the standard deviation of the series. A high ApEn indicates a complex, irregular series. A low ApEn indicates a regular series with less capacity to adapt.

Sample entropy (SampEn) was introduced by Richman and Moorman in 2000 [21]. It corrects a known bias of ApEn. When ApEn counts matching patterns, it also counts each pattern against itself. This self-match always succeeds and makes the series look more regular than it really is. SampEn excludes self-matches. It is therefore less biased than ApEn and depends less on series length, although estimates from short recordings remain variable [21]. SampEn may also be undefined when the series is very short or r is very small.

The values of m and r are chosen by the analyst. They are not biological constants. The same recording gives different entropy values with different r. Two studies can be compared only when they used the same parameters, and these parameters must be reported. We suggest reporting both indices. ApEn allows comparison with older studies, and SampEn has better statistical properties. When both move in the same direction, the conclusion is more reliable.

3.3.3. Fractal analysis: DFA-α1

Detrended fluctuation analysis (DFA) was introduced by Peng et al. in 1995 [22]. It measures something different from entropy, namely the correlation structure of the series. It describes whether fluctuations in one interval are correlated with those in earlier intervals, and over how many beats this correlation extends.

The exponent α can be read on a simple scale (Figure 2). A value near 0.5 describes an uncorrelated series, like white noise, in which each

interval is independent of the one before. A value near 1.5 describes a very smooth, strongly correlated series, similar to Brownian noise. A value near 1.0 lies between these extremes. It corresponds to fractal, 1/f-like behaviour, which is commonly observed in healthy adults at rest. Such a series is correlated over many time scales but still flexible [22, 23].

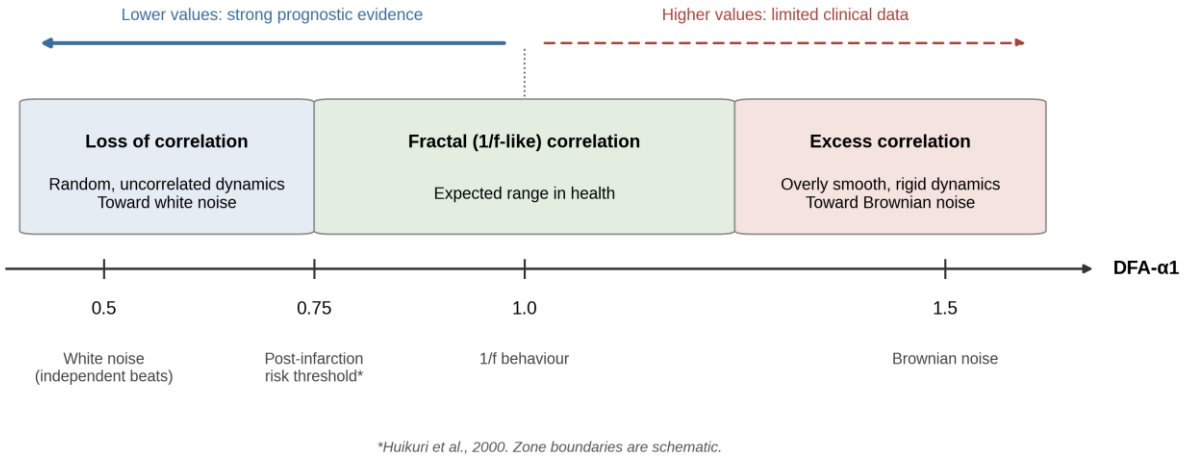


Figure 2. Schematic interpretation of DFA-α1. Values near 1.0 reflect fractal (1/f-like) correlation. Values toward 0.5 indicate loss of correlation, and values toward 1.5 indicate an overly smooth, strongly correlated series. Zone boundaries are schematic and are not validated cut-offs. The threshold of 0.75 comes from post-infarction data [24].

For DFA-α1, a higher value does not simply mean better regulation. Values near 1.0 are commonly reported in healthy adults at rest, and values further from 1.0 have been interpreted as altered correlation properties. The evidence is not equally strong for both directions. Low values are better documented. In the study by Huikuri et al. of 446 survivors of myocardial infarction with reduced ejection fraction, an α1 below 0.75 was the strongest HRV predictor of death. The relative risk was 3.0, and the association was independent of other risk markers [24]. Clinical data on high values are limited, and it has not been established whether a high α1 should be regarded as abnormal in diabetes.

DFA-α1 is calculated over short windows, usually 4 to 11 or 4 to 16 beats. It describes the short-term correlation properties of the NN series. These properties are influenced by vagal and baroreflex activity, but α1 is not a direct marker of either. The window range is a convention and differs between software packages. Values computed over different ranges should not be compared directly, so the range must be reported. DFA-α2 uses windows of about 16 to 64 beats. A five-minute recording gives only about 300 to 400 beats, which is usually too few for a stable estimate of α2. We therefore do not recommend reporting α2 from five-minute recordings [22].

Table 1. Main HRV indices from a five-minute resting recording, with proposed Vietnamese terms

Index (unit)	Domain	Physiological meaning	Typical change in CAN and notes	Proposed Vietnamese term
SDNN (ms)	Time	Total variability, both branches	Decreases; very low in advanced CAN	Độ lệch chuẩn của các khoảng NN
RMSSD (ms)	Time	Beat-to-beat change; vagal activity	Decreases early	Căn bậc hai trung bình bình phương hiệu các khoảng NN liên tiếp
HF (ms²)	Frequency	Respiratory oscillation; vagal activity	Decreases early	Công suất dải tần số cao
LF (ms²)	Frequency	Mainly baroreflex; mixed origin	Decreases in more advanced CAN	Công suất dải tần số thấp

Index (unit)	Domain	Physiological meaning	Typical change in CAN and notes	Proposed Vietnamese term
LF/HF	Frequency	Once used as sympathovagal balance	Not recommended for that purpose	Tỷ số LF/HF
SD1 (ms)	Nonlinear (geometric)	Short-term spread on the Poincaré plot; vagal activity	Decreases early; equals RMSSD/√2	Độ phân tán ngắn hạn trên biểu đồ Poincaré
SD2 (ms)	Nonlinear (geometric)	Long-term spread on the Poincaré plot	Decreases; derived from SDNN and SD1	Độ phân tán dài hạn trên biểu đồ Poincaré
ApEn	Nonlinear (entropy)	Irregularity of the NN series	Usually decreases; depends on m, r and scale	Entropy xấp xỉ
SampEn	Nonlinear (entropy)	As ApEn, without self-matches	As ApEn; less biased than ApEn in short series	Entropy mẫu
DFA-α1	Nonlinear (fractal)	Short-term correlation properties; values near 1.0 commonly reported in health	Low values best documented; meaning of high values uncertain	Số mũ tỷ lệ ngắn hạn của phân tích dao động loại bỏ xu hướng

3.4. Amplitude and structure: a working hypothesis

SDNN, RMSSD, HF and LF measure the absolute size of fluctuations, in milliseconds or ms². ApEn and SampEn describe irregularity, and DFA-α1 is a scaling exponent. Because these three indices are expressed relative to the structure of the signal rather than its size, they can in principle still vary when amplitude is markedly reduced. Whether this variation carries clinical information is uncertain.

On this basis, we propose a methodological hypothesis, which we call a floor effect. When fluctuations become very small, amplitude-based indices may crowd near the lower end of their range. Their spread would then narrow, and their ability to separate subgroups of patients would decrease. This is a hypothesis about measurement scales. It is neither an established property nor a cut-off. It may be relevant in older patients, in those with underlying heart disease and in long-standing type 2 diabetes. HRV falls with age [13] and is often reduced in patients with heart disease, including survivors of myocardial infarction [24]. In addition, the prevalence of CAN rises with disease duration and may exceed half of patients after 15 years [3, 4]. In such groups, nonlinear indices might keep more room to discriminate. This has not been tested directly. A direct test would compare amplitude and nonlinear indices across grades of CAN defined by CARTs.

Nonlinear indices have also been reported to change in milder metabolic disease. In a recent study by Zamora-Justo et al. of 278 adults, participants with the metabolic syndrome had lower resting SampEn and DFA values than those without metabolic alterations [25]. This study was cross-sectional, and it did not show that nonlinear indices add information beyond amplitude indices.

The direction of entropy change also needs care. The loss-of-complexity hypothesis, proposed by Lipsitz and Goldberger, holds that ageing and disease reduce the complexity of physiological signals [26]. However, multiscale entropy analysis by Costa et al. showed that entropy at short scales can increase when a system becomes disorganised, as in atrial fibrillation [23]. ApEn and SampEn are usually computed at short scales with m = 2. The direction of entropy change in a given population is therefore not always downward. Entropy should be read in context, not with a fixed rule that higher is better.

4. Recording conditions and common errors

HRV is sensitive to recording conditions. Differences in protocol can produce changes that are large relative to the differences reported between patient groups [13].

Minimum protocol. Record in the morning, in the supine position, after at least 10 minutes of rest in a quiet room at a stable temperature. The patient should not talk, should move as little as possible

and should breathe naturally. Record for at least five minutes. Note the time of recording and current medications. For follow-up, keep posture, time of day and device the same, because comparisons across different conditions are not valid [11, 12].

Confounders. The main confounders fall into four groups. These are fixed factors such as age, sex and ethnicity, diseases, lifestyle factors, and external factors such as heat and noise [13]. Several of them are directly relevant to diabetes clinics. Ectopic beats distort the NN series, especially RMSSD and entropy. Atrial fibrillation makes the series nearly random, and HRV should then not be read as an autonomic marker. Slow breathing, below about 9 breaths/min, shifts respiratory power into the LF band. Standing lowers HF and raises LF. Beta-blockers, anticholinergic drugs and tricyclic antidepressants change autonomic tone directly. Acute psychological stress and anxiety lower vagally mediated HRV, with reduced HF power reported most consistently [27]. Anxiety about the clinic visit or the test may therefore lower resting HRV. This is similar in principle to white-coat hypertension, although the size of the effect has not been quantified for HRV. Clinicians should ask about recent stress, allow the patient to settle and repeat a recording made while the patient was clearly anxious. Caffeine, smoking, meals and exercise should be avoided for at least two hours before recording [10, 13]. Table 2 shows how these factors should be documented.

Correction of ectopic beats. Ectopic beats are not always clinically apparent. Infrequent premature beats and asymptomatic arrhythmias may be missed or misclassified by automatic detection algorithms. Even a small number of ectopic beats can alter time-domain, frequency-domain and entropy measures, and the effect grows with their number [28]. Automatic beat detection should therefore be checked visually against the ECG tracing before indices are calculated [12]. Correction itself is not neutral for nonlinear indices. Every correction method replaces the removed interval with a value interpolated from neighbouring beats. The interpolated value is more regular than a real beat, so the corrected series is smoother than the true one. Entropy may therefore fall and DFA-α1 may rise artificially, and the bias is likely to grow with the number of corrected beats. Amplitude indices such as SDNN are affected less. When nonlinear indices are reported, the proportion of corrected beats and the correction method should be given in the results, not hidden in a methods appendix.

Devices. The ECG remains the reference method. The Polar H10 chest strap has been validated against the ECG for linear HRV indices at rest [29]. It is often paired with Kubios HRV, a widely used analysis package [30]. This combination served as the field reference in a recent validation study of a consumer smartwatch [31], and Kubios HRV Premium has been used with the Polar H10 in other research settings [32]. In our practice, we use the same combination. However, neither the Toronto consensus nor the current American Diabetes Association (ADA) Standards of Care endorses a specific commercial device or analysis software [3, 33]. Wrist devices based on photoplethysmography (PPG) are a different case. In a 10-day study of healthy volunteers, PPG-derived HRV was most accurate during sleep. During daily activities, its error was 14% to 51% higher than at rest, and posture and data quality also affected accuracy [34]. HRV from consumer PPG devices is not yet suitable for clinical decisions. Very short ECG recordings are also being explored. In the UK Biobank, RMSSD from ECG strips of 15 seconds or less agreed well with six-minute values and predicted cardiovascular events [35]. This is promising for screening, but similar data do not yet exist for nonlinear indices, which need longer series.

Age and heart rate. HRV falls with age and depends on mean heart rate. A low value in a 75-year-old does not mean the same as in a 40-year-old [10, 13]. Heart rate also changes what a given HRV value means. In 7,529 participants with type 2 diabetes from the Action to Control Cardiovascular Risk in Diabetes (ACCORD) trial, low SDNN was linked with higher mortality mainly when resting heart rate was also high [36]. Reference ranges must take both age and heart rate into account. This is also why the lack of Vietnamese reference values is a real limitation.

4.1. Minimum reporting checklist

Much of the difficulty in comparing HRV studies comes from incomplete reporting rather than from biology. Readers often cannot tell whether two results are comparable. Recent publication guidelines provide detailed checklists for heart rate and HRV research [12]. Table 2 condenses these points for clinical HRV reports in diabetes, with added detail for entropy and DFA. Applying it requires no extra equipment, only consistent record keeping.

Table 2. Minimum information to report in an HRV study or clinical HRV report

Item	What to report	Why it matters
Recording conditions	Posture, time of day, rest before recording, room temperature, spontaneous or paced breathing	Posture, circadian rhythm and breathing rate shift HF and LF
Patient state	Acute stress or anxiety; caffeine, smoking, meal or exercise in the previous 2 hours	Acute stress lowers vagally mediated HRV; stimulants and recent activity alter autonomic tone
Device	Type and model (e.g., Polar H10 chest strap), sampling rate, sensor position	ECG and PPG are not interchangeable; a low sampling rate adds error
Recording	Duration, number of analysable beats, proportion of sinus beats	Five-minute and 24-hour indices differ; short series limit entropy and DFA
Pre-processing	Method for detecting and correcting ectopic beats, proportion of corrected beats, detrending method and settings, interpolation before spectral analysis; whether automatic beat detection was checked visually	Missed or uncorrected ectopic beats distort all domains; correction smooths the series and biases nonlinear indices
Frequency domain	FFT or AR method, units (ms^2 or n.u.), band limits	Method and units change values and meaning
Entropy	m and r, and how r was defined	Values are comparable only with identical parameters
DFA	Window range for α1 in beats; state that α2 was not computed from short recordings, and why	Different ranges give non-comparable α1 values
Software	Name and version (e.g., Kubios HRV Premium), correction settings	Default settings differ between packages
Patient context	Age, sex, mean heart rate, drugs that affect autonomic tone, arrhythmia	HRV depends on age and heart rate; drugs alter autonomic tone; atrial fibrillation invalidates interpretation

5. HRV alongside cardiovascular autonomic reflex tests

5.1. Comparison with cardiovascular autonomic reflex tests

Current evidence does not support replacing the Ewing battery with resting HRV, and the main reason is physiological.

The classic battery described by Ewing comprises five tests [3, 4]. These are the heart rate response to deep breathing, the heart rate response to standing (30:15 ratio), the heart rate response to the Valsalva manoeuvre (Valsalva ratio), the blood pressure response to standing and the blood pressure response to sustained handgrip. The first three tests assess cardiovagal function, and the last two assess sympathetic function. The Toronto consensus grades CAN by the number of abnormal heart rate tests. One abnormal test indicates possible or early CAN. Two or more indicate definite CAN. Orthostatic hypotension in addition to abnormal heart rate tests indicates severe or advanced CAN [3]. Sustained handgrip is not part of this grading. Fixed resting tachycardia is common in advanced disease, but it is not a grading criterion either.

CARTs and resting HRV do not measure the same thing. Resting HRV describes baseline autonomic modulation. CARTs are provocative (challenge) tests that apply a standard stimulus. The Valsalva and standing tests challenge the baroreflex and sympathetic vasoconstriction. The test for orthostatic hypotension assesses the ability to hold blood pressure when blood volume shifts. A five-minute supine recording does not reach these responses. So low HRV does not equal definite CAN, and normal HRV does not exclude impaired sympathetic responses.

Nevertheless, the two approaches are closer than their names suggest. The deep-breathing test is in essence an HRV measurement. It quantifies the difference in heart rate between inspiration and expiration, which is RSA. HRV therefore extends a principle that the battery already uses, rather than competing with it as an outside method.

Studies that compared the two approaches support a screening role for HRV. Pop-Busui et al. examined 311 people with type 1 diabetes from the Diabetes Control and Complications Trial/Epidemiology of Diabetes Interventions and Complications (DCCT/EDIC) cohort. ECG-derived SDNN showed fair agreement with CART-defined CAN, with an area under the curve of 0.73 [37]. Oliveira et al. studied 50 adults with prediabetes or type 2 diabetes. Resting HF power had a sensitivity of 67.9% and a specificity of 86.4% for CAN [9]. These figures are acceptable for triage but not for a final diagnosis, and data from type 2 diabetes are still limited.

On this basis, we propose a pragmatic framework in which resting HRV could serve as a first-line tool for screening and follow-up, while CARTs are used to confirm and grade CAN (Figure 3). This framework is the authors' proposal and not a validated clinical algorithm. Its performance, including the HRV level at which CARTs should be requested, needs prospective testing. It is intended to avoid two opposite errors: missing patients because CARTs cannot be done for everyone, and diagnosing CAN from a single low HRV value.

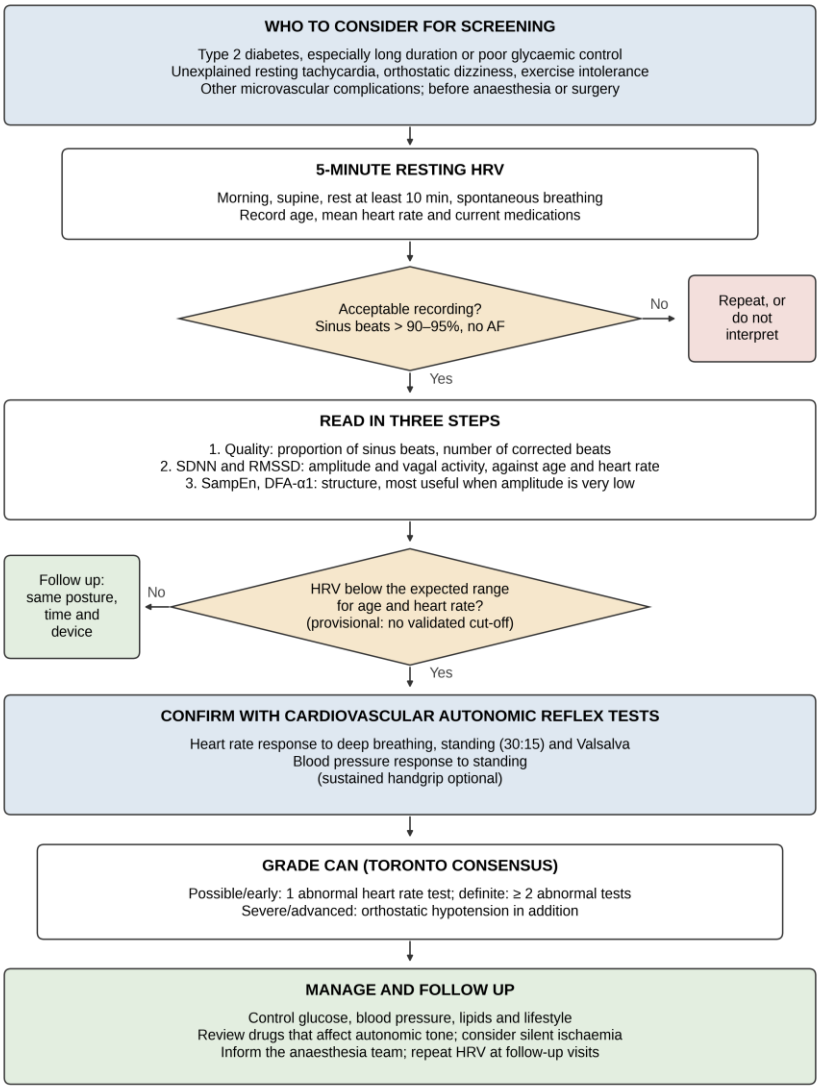


Figure 3. Proposed pragmatic framework for assessing cardiac autonomic neuropathy, with HRV for screening and CARTs for confirmation. This is the authors' proposal, not a validated clinical algorithm. The comparison with the expected range is provisional, because validated cut-offs are not yet available. AF, atrial fibrillation; CAN, cardiac autonomic neuropathy; CARTs, cardiovascular autonomic reflex tests; DFA-α1, short-term scaling exponent of detrended fluctuation analysis; HRV, heart rate variability; RMSSD, root mean square of successive differences; SampEn, sample entropy; SDNN, standard deviation of NN intervals.

5.2. Clinical applications reported to date

Studies of HRV in diabetes have used it for different clinical purposes, and the strength of evidence differs between them. Diagnostic comparisons with CARTs are described in Section 5.1.

Home and remote monitoring. Poulsen et al. tested a contactless ECG sheet that records an ECG-derived index of cardiac vagal tone during sleep. In 40 people with type 2 diabetes and 20 controls, signal quality was high over three nights at home. Cardiac vagal tone was lower in diabetes, and it identified any or manifest CAN with areas under the curve of 0.64 to 0.79. Detection of early CAN was poor [38]. Ultra-short ECG recordings are another option for large-scale screening (Section 4) [35].

Monitoring response to treatment. HRV has been used as an outcome in intervention studies. A meta-analysis by Picard et al. included 21 studies of exercise training in patients with type 2 diabetes. Training increased SDNN, RMSSD and pNN50, with moderate effect sizes, while no changes were seen in control groups [39]. These data suggest that HRV can track changes in autonomic modulation, but they do not show that such changes improve clinical outcomes.

Risk stratification and perioperative care. Prognostic studies in type 2 diabetes are reviewed in Section 6. Before surgery, autonomic imbalance has been linked with haemodynamic instability and postoperative complications [8], but evidence specific to type 2 diabetes remains limited.

Overall, HRV has been studied for detection, monitoring and risk stratification. In our search, we did not identify a study showing that an HRV-based strategy changes management or improves outcomes in type 2 diabetes.

6. HRV and cardiovascular risk: Evidence and limits

6.1. What the evidence supports

CAN defined by CARTs is linked with higher cardiovascular and all-cause mortality, although reported five-year mortality in advanced CAN varies widely between studies [1, 2]. Data on HRV itself come from recordings of different lengths, and their results are not interchangeable. We therefore group them by recording type.

Long-term (24-hour) recordings. Reduced HRV in type 2 diabetes is well established. Benichou et al. pooled 25 case-control studies with 2,932 participants in a meta-analysis of 24-hour recordings. They found lower SDNN, RMSSD, pNN50, total power, LF and HF in patients with diabetes. Glucose, glycated haemoglobin (HbA1c) and time since diagnosis were related to several indices [19]. In the population-based Maastricht Study (n = 2,107), Coopmans et al. found that HRV was lower in prediabetes and lower still in type 2 diabetes. For the time-domain score, the adjusted standardised β was - 0.15 in prediabetes and - 0.34 in diabetes [5]. These data are cross-sectional.

Night-time Holter data. In the Copenhagen Holter Study, Hadad et al. showed that people with well-controlled type 2 diabetes and lower night-time SDNN had more cardiovascular events over a median follow-up of 14 years. Adding night-time SDNN to conventional risk factors raised the area under the curve from 0.70 to 0.77 [7].

Short and ultra-short resting recordings. A meta-analysis of short-term recordings by Ortiz-Guzmán et al. found lower HRV in the metabolic syndrome [6]. In the ACCORD trial, Huang et al. used HRV from resting ECGs and reported that the combination of low SDNN and high resting heart rate was associated with higher all-cause mortality [36]. In the UK Biobank, RMSSD from ECG strips of 15 seconds or less predicted cardiovascular events [35]. In contrast, in the Whitehall II study, Hansen et al. found that five-year changes in five-minute HRV did not predict cardiovascular disease or death in people with or without dysglycaemia [40]. Prognostic data from standard five-minute recordings in type 2 diabetes are therefore limited and not fully consistent.

Data extrapolated from other populations. Among nonlinear indices, the clearest prognostic data concern DFA-α1 from Holter recordings after myocardial infarction [24]. These data come from a different population and a different recording length, and they should not be applied directly to five-minute recordings in diabetes.

6.2. What the evidence does not yet allow

Several limits should be considered before these findings are applied in practice.

First, most of the evidence is observational, and much of it is cross-sectional. The link between low HRV and cardiovascular events is fairly consistent, but not all cohorts agree (Section 6.1). In our search, we did not identify an intervention trial showing that measuring HRV improves patient outcomes. This is the difference between a

prognostic marker and a test with proven clinical value.

Second, validated cut-offs are lacking for most indices, and especially for nonlinear ones. Studies differ in device, software, recording length and calculation parameters. Direct comparison between them is often not valid.

Third, HRV depends on age, sex, heart rate, drugs and many comorbidities [13]. A single value taken out of its clinical context carries limited information.

Fourth, there are no reference values for the Vietnamese population. Borrowing ranges from European or North American populations is a temporary solution. It should be stated as a limitation in every report.

Because of the second point, we deliberately did not compile a table of reference values for nonlinear indices. Pooling means from studies with different m, r, DFA windows and recording lengths would produce a convincing table with no basis for comparison. Readers who need numbers should go to the original study whose design is closest to their own setting. They should also check the calculation parameters before using the values.

HRV is an accessible physiological marker with possible value for screening and risk stratification, but it is not a stand-alone diagnostic test. Overstating its role could lead to disappointment and to a useful tool being abandoned.

7. Practical use and gaps in Vietnam

7.1. Who should be measured and how to read the result

Both the Toronto panel and current ADA standards support assessment for autonomic neuropathy from the time type 2 diabetes is diagnosed [3, 33]. Based on the evidence above, HRV assessment may be considered in several groups. The first is people with type 2 diabetes, especially those with long disease duration or poor glycaemic control. The second is patients with unexplained resting tachycardia, orthostatic dizziness or exercise intolerance. The third is patients with other diabetic microvascular complications, such as retinopathy or peripheral neuropathy. The last is patients with long-standing diabetes who are scheduled for anaesthesia or invasive procedures. In this setting, information on autonomic reserve may help plan haemodynamic monitoring.

We suggest reading the results in three steps. Step one is to check recording quality before looking at any number. This covers the proportion of sinus beats, the number of corrected beats and the absence of atrial fibrillation. A poor-quality recording can still produce plausible-looking values. Step two is to read SDNN and RMSSD for overall amplitude and vagal activity, with reference to age and heart rate. Step three is to read the nonlinear indices for the structure of regulation, especially when amplitude indices are already very low. If the result suggests an abnormality, the next step is CARTs for confirmation. A diagnosis should not be made from HRV alone. This reading sequence reflects the authors' approach and has not been validated.

7.2. Gaps in Vietnam and research priorities

Published Vietnamese HRV studies, by Nguyen Hoanh Cuong [14], Truong Dinh Cam and Pham Toan Trung [15], and Tran Thi Tam and Pham Tran Linh [16], focused on type 2 diabetes with various complications, and their results point in the same direction. Time- and frequency-domain indices were clearly lower in patients with chronic complications and were related to glycaemic control. All of these studies were limited to the time and frequency domains, and we did not identify Vietnamese studies of entropy or fractal indices. As discussed in Section 3.4, these indices might retain discriminating ability in patients with very low HRV, but this needs testing. In addition, nonlinear indices have no agreed Vietnamese names, which makes teaching and clinical discussion harder. We propose Vietnamese equivalents for the main indices in Table 1. For example, we suggest “entropy mẫu” for sample entropy, “entropy xấp xỉ” for approximate entropy and “phân tích dao động loại bỏ xu hướng” for detrended fluctuation analysis. We recommend keeping the international abbreviations in tables and using the Vietnamese terms in teaching and in Vietnamese-language texts.

Three research priorities follow. The first is to establish age- and sex-specific HRV reference ranges for healthy Vietnamese adults. The second is to measure all three domains together in different patient groups, to find out which domain discriminates best at each stage of disease. The third is to test the value of HRV for perioperative risk stratification. This application meets a clear practical need, but we did not identify Vietnamese studies of it.

8. Conclusion

HRV is a non-invasive, low-cost measure that is easy to standardise. It can detect reduced cardiac autonomic modulation before symptoms appear. Time- and frequency-domain indices describe the amplitude of fluctuations, and nonlinear indices describe their organisation. Whether nonlinear indices add information when amplitude is very low remains a hypothesis that needs direct testing.

Current evidence supports CARTs as the reference for diagnosing CAN. We propose that HRV could serve as a screening and follow-up tool, but this framework needs prospective validation. Because recording conditions strongly affect HRV, standard protocols and complete technical reporting should be treated as requirements, not options.

The current limits should be stated plainly. The evidence is mostly observational, validated cut-offs are lacking, and there are no Vietnamese reference values. Two steps are needed to move HRV from a research marker to a reliable clinical tool in Vietnam. The first is to study all three domains together. The second is to build local reference data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-Assisted Technologies

Artificial intelligence tools were used to assist in the creation and design of figures and illustrations for this manuscript. All figures were reviewed and approved by the authors.

Author Contributions

Ngoc Hien Tran: Conceptualization, study design, literature collection and synthesis, data analysis, and manuscript drafting. Linh Ly Luong, Trong Nhan Le: Scientific supervision, contributions to study design, manuscript review, and editing. Hong Tam Nhan: Assistance with literature collection and data synthesis, and contributions to manuscript revision. Quoc Tuan Le: Corresponding author, responsible for communication with the journal and coordination of the manuscript submission and publication process. All authors read and approved the final manuscript.

Refrences

1. Eleftheriadou A, Spallone V, Tahrani AA, et al. Cardiovascular autonomic neuropathy in diabetes: an update with a focus on management. Diabetologia. 2024;67(12):2611-25.

2. Williams S, Raheim SA, Khan MI, et al. Cardiac autonomic neuropathy in type 1 and 2 diabetes: epidemiology, pathophysiology, and management. Clin Ther. 2022;44(10):1394-416.

3. Spallone V, Ziegler D, Freeman R, et al. Cardiovascular autonomic neuropathy in diabetes: clinical impact, assessment, diagnosis, and management. Diabetes Metab Res Rev. 2011;27(7):639-53.

4. Gogan A, Potre O, Avram VF, et al. Cardiac autonomic neuropathy in diabetes mellitus: pathogenesis, epidemiology, diagnosis and clinical implications: a narrative review. J Clin Med. 2025;14(3):671.

5. Coopmans C, Zhou TL, Henry RMA, et al. Both prediabetes and type 2 diabetes are associated with lower heart rate variability: the Maastricht Study. Diabetes Care. 2020;43(5):1126-33.

6. Ortiz-Guzmán JE, Mollà-Casanova S, Serra-Añó P, et al. Short-term heart rate variability in metabolic syndrome: a systematic review and meta-analysis. J Clin Med. 2023;12(18):6051.

7. Hadad R, Larsen BS, Weber P, et al. Night-time heart rate variability identifies high-risk people among people with uncomplicated type 2 diabetes mellitus. Diabet Med. 2021;38(7):e14559.

8. Pan WT, Ji MH, Ma D, Yang JJ. Effect of perioperative autonomic nervous system imbalance on surgical outcomes: a systematic review. Br J Anaesth. 2025;135(3):608-22.

9. Oliveira DPSC, Souza CAQS, Facchin AC, et al. Diagnostic value of heart rate-based methods for assessing cardiac autonomic neuropathy in prediabetes and diabetes. Physiol Rep. 2025;13(19):e70610.

10. Shaffer F, Ginsberg JP. An overview of heart rate variability metrics and norms. Front Public Health. 2017;5:258.

11. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Heart rate variability: standards of measurement,

physiological interpretation and clinical use. Circulation. 1996;93(5):1043-65.

12. Quigley KS, Gianaros PJ, Norman GJ, et al. Publication guidelines for human heart rate and heart rate variability studies in psychophysiology-Part 1: physiological underpinnings and foundations of measurement. Psychophysiology. 2024;61(9):e14604.

13. Sammito S, Thielmann B, Böckelmann I. Update: factors influencing heart rate variability-a narrative review. Front Physiol. 2024;15:1430458.

14. Nguyễn Hoành Cường. Study of heart rate variability indices and cardiac arrhythmias in patients with type 2 diabetes and kidney damage [dissertation, in Vietnamese]. Hanoi: Vietnam Military Medical University; 2014.

15. Trương Đình Cẩm, Phạm Toàn Trung. Heart rate variability indices in patients with type 2 diabetes and chronic heart failure [in Vietnamese]. Journal of 108 Clinical Medicine and Pharmacy. 2018;13(6):62-9.

16. Trần Thị Tâm, Phạm Trần Linh. Heart rate variability in patients with type 2 diabetes and unstable blood glucose [in Vietnamese]. Vietnam Medical Journal. 2021;507(1):133-7.

17. Amekran Y, Damoun N, El Hangouche AJ. Analysis of frequency-domain heart rate variability using absolute versus normalized values: implications and practical concerns. Front Physiol. 2024;15:1470684.

18. Billman GE. The LF/HF ratio does not accurately measure cardiac sympatho-vagal balance. Front Physiol. 2013;4:26.

19. Benichou T, Pereira B, Mermillod M, et al. Heart rate variability in type 2 diabetes mellitus: a systematic review and meta-analysis. PLoS One. 2018;13(4):e0195166.

20. Pincus SM. Approximate entropy as a measure of system complexity. Proc Natl Acad Sci U S A. 1991;88(6):2297-301.

21. Richman JS, Moorman JR. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circ Physiol. 2000;278(6):H2039-49.

22. Peng CK, Havlin S, Stanley HE, Goldberger AL. Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. Chaos. 1995;5(1):82-7.

23. Costa M, Goldberger AL, Peng CK. Multiscale entropy analysis of complex physiologic time series. Phys Rev Lett. 2002;89(6):068102.

24. Huikuri HV, Mäkikallio TH, Peng CK, et al. Fractal correlation properties of R-R interval dynamics and mortality in patients with depressed left ventricular function after an acute myocardial infarction. Circulation. 2000;101(1):47-53.

25. Zamora-Justo JA, Campos-Aguilar M, Beas-Jara MC, et al. Utility of nonlinear analysis of heart rate variability in early detection of metabolic syndrome. Front Physiol. 2025;16:1597314.

26. Lipsitz LA, Goldberger AL. Loss of 'complexity' and aging: potential applications of fractals and chaos theory to senescence. JAMA. 1992;267(13):1806-9.

27. Kim HG, Cheon EJ, Bai DS et al. Stress and heart rate variability: a meta-analysis and review of the literature. Psychiatry Investig. 2018;15(3):235-45.

28. Zhao L, Li P, Li J, Liu C. Influence of ectopic beats on heart rate variability analysis. Entropy (Basel). 2021;23(6):648.

29. Schaffarczyk M, Rogers B, Reer R, Gronwald T. Validity of the Polar H10 sensor for heart rate variability analysis during resting state and incremental exercise in recreational men and women. Sensors (Basel). 2022;22(17):6536.

30. Tarvainen MP, Niskanen JP, Lipponen JA, et al. Kubios HRV: heart rate variability analysis software. Comput Methods Programs Biomed. 2014;113(1):210-20.

31. O'Grady B, Lambe R, Baldwin M, Acheson T, Doherty C. The validity of Apple Watch Series 9 and Ultra 2 for serial measurements of heart rate variability and resting heart rate. Sensors (Basel). 2024;24(19):6220.

32. Rogers B, Schaffarczyk M, Gronwald T. Estimation of respiratory frequency in women and men by Kubios HRV software using the Polar H10 or Movesense Medical ECG sensor during an exercise ramp. Sensors (Basel). 2022;22(19):7156.

33. American Diabetes Association Professional Practice Committee for Diabetes. 12. Retinopathy, neuropathy, and foot care: Standards of Care in Diabetes-2026. Diabetes Care. 2026;49(Suppl 1):S261-76.

34. Zia Ur Rehman R, Chatterjee M, Manyakov NV, et al. Assessment of physiological signals from photoplethysmography sensors compared to an electrocardiogram sensor: a validation study in daily life. Sensors (Basel). 2024;24(21):6826.

35. Orini M, van Duijvenboden S, Young WJ, et al. Long-term association of ultra-short heart rate variability with cardiovascular events. Sci Rep. 2023;13(1):18966.

36. Huang Y, Xie P, Zhang S, et al. Interplay of heart rate variability and resting heart rate on mortality in type 2 diabetes. Diabetes Metab Syndr. 2024;18(1):102930.

37. Pop-Busui R, Backlund JC, Bebu I, et al. Utility of using electrocardiogram measures of heart rate variability as a measure of cardiovascular autonomic neuropathy in type 1 diabetes patients. J Diabetes Investig. 2022;13(1):125-33.

38. Poulsen MB, Julu P, Røikjer J, et al. The ProCVT smart-sheet as a new screening tool for cardiovascular autonomic neuropathy: a feasibility study. Front Endocrinol (Lausanne). 2025;16:1653881.

39. Picard M, Tauveron I, Magdasy S, et al. Effect of exercise training on heart rate variability in type 2 diabetes mellitus patients: a systematic review and meta-analysis. PLoS One. 2021;16(5):e0251863.

40. Hansen CS, Jørgensen ME, Malik M, et al. Heart rate and heart rate variability changes are not related to future cardiovascular disease and death in people with and without dysglycemia: a downfall of risk markers? The Whitehall II cohort study. Diabetes Care. 2021;44(4):1012-9.

BIẾN THIÊN NHỊP TIM TRONG ĐÁNH GIÁ CHỨC NĂNG THẦN KINH TỰ CHỦ TIM Ở BỆNH NHÂN ĐÁI THÁO ĐƯỜNG TÍP 2: TỪ MIỀN THỜI GIAN, MIỀN TẦN SỐ ĐẾN PHÂN TÍCH PHI TUYẾN

Ngọc Hiến Trần[1], Trọng Nhân Lê[2], Linh Ly Lương[2], Hồng Tâm Nhan[2], Quốc Tuấn Lê[1]*

[1] Trường Đại học Y Dược Thành phố Hồ Chí Minh

[2] Trường Đại học Quốc tế Hồng Bàng

TÓM TẮT

Rối loạn thần kinh tự chủ tim (CAN) là biến chứng thường gặp của đái tháo đường típ 2 và thường chỉ được phát hiện khi đã có biến cố tim mạch. Bộ nghiệm pháp phản xạ tim mạch (CARTs) là tiêu chuẩn chẩn đoán nhưng cần thời gian, nhân lực được huấn luyện và sự hợp tác của người bệnh. Phân tích biến thiên nhịp tim (HRV) từ bản ghi nghỉ năm phút nhanh, không xâm lấn và chi phí thấp. Bài tổng quan này phân tích HRV theo ba miền: thời gian, tần số và phi tuyến. Bài viết bàn về vị trí của HRV so với CARTs, tóm tắt bằng chứng ứng dụng lâm sàng và giá trị tiên lượng ở bệnh nhân đái tháo đường típ 2, đồng thời đề xuất quy trình đo chuẩn và danh mục báo cáo tối thiểu. Chúng tôi đề xuất HRV phù hợp cho sàng lọc và theo dõi, còn chẩn đoán CAN vẫn dựa vào CARTs; khung tiếp cận này chưa được thẩm định. Chỉ số miền thời gian và tần số đo biên độ dao động nhịp tim, còn chỉ số phi tuyến mô tả cách tổ chức của dao động. Chúng tôi giả thuyết rằng chỉ số phi tuyến có thể còn khả năng phân biệt ở giai đoạn nặng, khi chỉ số biên độ đã dồn sát giới hạn dưới; giả thuyết này chưa được kiểm chứng. Phần lớn chỉ số chưa có ngưỡng cắt được kiểm chứng và chưa có giá trị tham chiếu cho người Việt Nam. Vì vậy, chuẩn hóa quy trình đo và báo cáo là điều kiện để HRV trở thành công cụ lâm sàng đáng tin cậy.

Từ khóa: biến thiên nhịp tim, bệnh thần kinh tự chủ tim, đái tháo đường típ 2.