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Assessment of the relational strength between triggers detected in physiological signals and the occurrence of atrial fibrillation episodes

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Abstract

Objective. Despite the growing interest in understanding the role of triggers of paroxysmal atrial fibrillation (AF), solutions beyond questionnaires to identify a broader range of triggers remain lacking. This study aims to investigate the relation between triggers detected in wearable-based physiological signals and the occurrence of AF episodes. *Approach.* Week-long physiological signals were collected during everyday activities from 35 patients with paroxysmal AF, employing an ECG patch attached to the chest and a photoplethysmogram (PPG)-based wrist-worn device. The signals acquired by the patch were used for detecting potential triggers due to physical exertion, psychophysiological stress, lying on the left side, and sleep disturbances. To assess the relation between detected triggers and the occurrence of AF episodes, a measure of relational strength is employed accounting for pre- and post-trigger AF burden. The usefulness of ECG- and PPG-based AF detectors in determining AF burden and assessing the relational strength is also analyzed. *Main results.* Physical exertion emerged as the trigger associated with the largest increase in relational strength for the largest number of patients ($p < 0.01$). On the other hand, no significant difference was observed for psychophysiological stress and sleep disorders. The relational strength of the detected AF exhibits a moderate correlation with the relational strength of annotated AF, with $r = 0.66$ for ECG-based AF detection and $r = 0.62$ for PPG-based AF detection. *Conclusions.* The findings indicate a patient-specific increase in relational strength for all four types of trigger. *Significance.* The proposed approach has the potential to facilitate the implementation of longitudinal studies and can serve as a less biased alternative to questionnaire-based AF trigger detection.

1. Introduction

Despite advances in arrhythmia treatment, atrial fibrillation (AF) management remains a complex challenge (Lippi *et al* 2021). The options for AF management are often confined to oral anticoagulants and antiarrhythmic medication, each with notable side effects (Zimetbaum 2012, Mani and Lindhoff-Last 2014). On the other hand, current treatment, for example, catheter ablation, come with substantial costs and a risk of AF recurrence following intervention (Marine 2021). Therefore, an effective strategy may involve interventions targeting lifestyle and risk factors in conjunction with conventional approaches to AF management (Chung *et al* 2020).

AF leads to electrical and structural changes in the atria; thus, the goal is to maintain sinus rhythm for as long as possible (Van Gelder and Hemels 2006). According to the latest understanding of AF initiating mechanisms, AF episodes occur due to the interplay between the arrhythmogenic substrate, modulating factors, and acute exposures, often referred to as AF triggers (Vincenti *et al* 2006, Nattel and Dobrev 2016, Severino *et al* 2019). AF triggers are gaining research interest due to their potential role in initiating AF in certain patients (Groh *et al* 2019). Therefore, patient-specific detection of triggers may become an important aspect of personalized AF management, enabling clinicians to focus on the underlying causes of AF episodes in individual patients. In addition, patients can actively participate in managing their AF by making lifestyle changes. Nevertheless, solutions to reliably detect a broader range of triggers are lacking.

Among the many AF triggers (Hansson *et al* 2004, Groh *et al* 2019), alcohol is the most extensively studied, consistently demonstrating an association with the occurrence of AF episodes (Marcus *et al* 2022). Abstaining from alcohol for several months reduces arrhythmia recurrence twofold in habitual drinkers (Voskoboinik *et al* 2020), while consuming two or more standard alcoholic beverages is associated with a threefold increase in the prevalence of AF within the next four hours (Marcus *et al* 2021). Evidence suggests that the occurrence of AF episodes is also associated with physical exertion (Abdulla and Nielsen 2009, Guasch and Mont 2017), lying on the left side (Gottlieb *et al* 2021b), psychophysiological stress (Leo *et al* 2023), and sleep disorders (Mehra *et al* 2022, Wong *et al* 2024).

The main limitation of prior studies lies in the subjectivity of AF triggers, as they were predominantly self-reported through the use of questionnaires (Hansson *et al* 2004, Groh *et al* 2019, Voskoboinik *et al* 2020, Marcus *et al* 2022). A considerable number of AF patients could identify a few trigger types, suggesting confirmation bias (Groh *et al* 2019). Conversely, the fact that certain triggers were not reported by some patients may be attributed to recall bias, for example, reluctance to acknowledge triggers which are bad for health, like alcohol consumption (Groh *et al* 2019). An early effort to reduce questionnaire-related bias involved a wearable ECG monitor and a transdermal alcohol sensor to supplement self-reported instances of alcohol consumption with objective data (Marcus *et al* 2021).

Thanks to technological advancements, wearable devices are today equipped with biosensors capable of acquiring various physiological signals useful for detecting AF triggers and gathering AF episodes with the same device. However, the detection of AF episodes is a much more complex task than merely confirming the existence of arrhythmia (Butkuvienė *et al* 2024). It necessitates long-term, uninterrupted monitoring, where interruptions or poor signal quality result in lost information on the occurrence of AF episodes, thereby complicating the assessment of trigger interaction. Presently, implantable devices and ECG patches (e.g. Zio XT Patch, Bittium Faros, Biobeat chest monitor) are the only commercial alternatives that ensure reliable long-term monitoring. Conversely, wrist-worn devices capable of acquiring a photoplethysmogram (PPG) are less accurate in detecting AF (Sološenko *et al* 2019, Zhu *et al* 2021), albeit more convenient. Nonetheless, no study has yet investigated the detection of triggers in physiological signals, let alone the integration of trigger information with the occurrence of AF episodes.

The present study proposes and explores a novel approach to establishing the relation between triggers detected in long-term physiological signals and the occurrence of AF episodes. The method is designed to detect triggers due to physical exertion, psychophysiological stress, lying on the left side, and sleep disturbances in physiological signals. For the first time, the recently proposed measure of relational strength between triggers and the occurrence of AF episodes (Pluščiauskaitė *et al* 2024) is applied to week-long ECG and PPG signals collected from patients diagnosed with paroxysmal AF when doing their daily activities. To gain insight into the utility of wearable devices for assessing relational strength, both ECG- and PPG-based AF detectors are employed. Due to the limited understanding of how triggers influence the occurrence of AF episodes in individual patients, the present study represents a step towards comprehending the mechanisms governing trigger effects on AF episodes.

2. Methods

2.1. Database

One hundred eighty two patients diagnosed with paroxysmal AF were recruited from inpatient and outpatient wards of the Cardiology Department at Vilnius University Hospital Santaros Klinikos. Prior to their involvement, all eligible patients provided signed, written informed consent in agreement with the ethical principles of the Declaration of Helsinki. Approval of the study was granted by the Vilnius Regional Bioethics Committee (Reference Number 158200-18/7-1052-557). Only patients with at least one AF episode during the observation interval were included, resulting in a database of 35 patients, see table 1.

The database is comprised of physiological signals recorded during daily activities, using a Bittium OmegaSnap^{TM} one channel ECG patch (Bittium, Finland), and a wrist-worn device developed at the Biomedical Engineering Institute of Kaunas University of Technology (Bacevičius *et al* 2022). The ECG patch was positioned directly on the sternum to record a continuous ECG sampled at 500 Hz and tri-axial acceleration signals sampled at 25 Hz. The wrist-worn device captured a continuous PPG sampled at 100 Hz. The signal database is available on Zenodo (Bacevičius *et al* 2024).

Table 1. Demographic and clinical characteristics of patients with paroxysmal AF.

Women, *n*	21
Men, *n*	14
Age, yrs	61 ± 13
Height, cm	175 ± 10
Weight, kg	89 ± 20
Body mass index, kg m^{-2}	28.4 ± 5.0
Observation interval, days	7.0 ± 0.7
Medication (#patients)	
Beta adrenoblockers	26
Antihypertensive drugs	31
Comorbidities (#patients)	
Hypertension	29
Hyperthyroidism	3
Metabolic syndrome	15

2.2. AF detection

2.2.1. Annotation of AF episodes

A preliminary annotation of AF episodes was provided using the ECG-based detector described below, followed by a manual review to refine the annotations by searching for undetected episodes, excluding falsely detected episodes, and improving the temporal precision of episode onset and end. Cardiology residents performed the manual review, consulting an experienced cardiologist in uncertain cases. The residents annotated premature atrial contractions, atrial tachycardia, and atrial flutter.

2.2.2. Detector-based AF episodes

Two AF detectors are employed, one relying on the ECG and the other on the PPG. The ECG-based detector relies on the fact that the RR intervals during AF are irregular and often associated with an elevated heart rate (HR) (Petrėnas *et al* 2015). The detector, designed to find short AF episodes, incorporates ectopic beat removal, suppression of bigeminy, quantification of RR interval irregularity, and signal fusion.

Poor-quality ECG segments are excluded from further analysis. The assessment of signal quality relies on the *bsqi* index which explores the difference in performance of two different QRS detectors (Behar *et al* 2013). The first detector (*jqrs*) is from the PhysioNet Cardiovascular Toolbox (Vest *et al* 2018), whereas the second detector is from the R-DECO toolbox (Moeyersons *et al* 2019). The index is defined by the percentage of beats aligning between the two detectors, here set to 90% if a segment is to be considered for further analysis. Moreover, only segments without premature atrial contractions, atrial flutter, and atrial tachycardia are analyzed.

The PPG-based detector relies on the analysis of peak-to-peak intervals, using an adaptive threshold for peak detection (Sološenko *et al* 2019). The detector incorporates the same signal processing blocks as the ECG-based detector aimed at reducing the number of false alarms. The detector includes a block for assessment of signal quality.

Both AF detectors offer flexibility in determining the minimum episode duration, controlled by the smoothing coefficient of exponential averaging filters; for details, see Petrėnas *et al* (2015). In this study, the smoothing coefficient was set to 0.02, resulting episodes as brief as 60 beats. Given that HR often increases during AF, this duration is in agreement with the clinical definition of the minimum episode duration (Kirchhof *et al* 2016).

The annotated and detector-based AF episodes are exemplified in figure 1. It is should be noted that the ECG-based AF detector emphasizes sensitivity, while the PPG-based detector emphasizes specificity. As a result, ECG-based AF detection may produce more falsely detected episodes, while PPG-based AF detection may miss some episodes due to preferred specificity.

2.3. Trigger detection

The principles for detecting potential triggers are described in the following. Each type of trigger is based on a detection parameter computed in successive intervals throughout the ECG and/or acceleration signals, resulting in a time series which is subject to threshold-based detection. For simplicity, physical exertion, psychophysiological stress, lying on the left side, and sleep disturbances are in the following referred to as triggers irrespective of whether AF occurs or not.

2.3.1. Physical exertion

Participating in higher-intensity exercise is considered a contributing factor to the occurrence of AF episodes, both in athletes and the general population (Shamloo *et al* 2018). To detect physical exertion, the metabolic

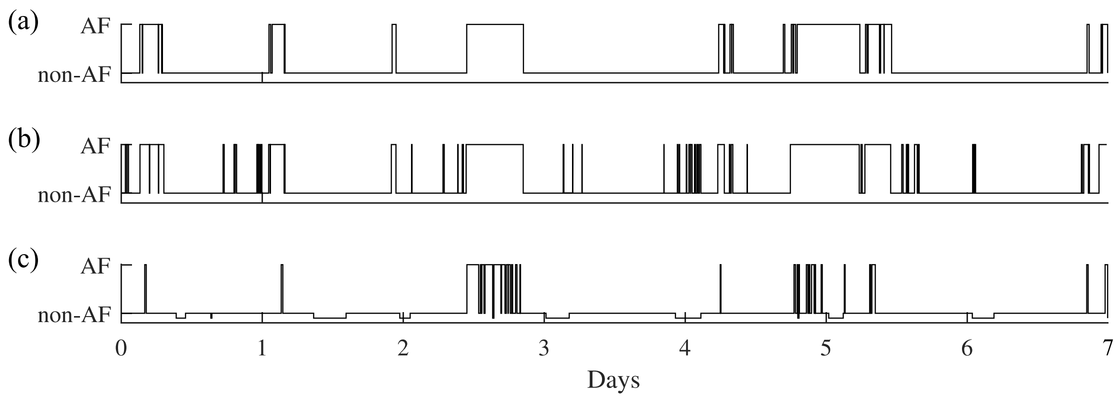

Figure 1. An example of AF episodes obtained by (a) annotation, (b) ECG-based detection, and (c) PPG-based detection. (c) Dropouts, indicated by a lowered non-AF baseline, represent non-wear time of the PPG device.

equivalent of task (MET), serving as a physiological measure of the energy expenditure associated with various physical activities relative to the resting metabolic rate, is used for detecting physical exertion.

The MET is estimated using acceleration and HR to account for patient-specific variability, as patients may exhibit different HR responses to the same physical activity due to variation in fitness level and health condition. The following regression equation is used to estimate MET (Moeyersons *et al* 2019):

$$y_{\mathrm{MET}} = 0.0043x_{\mathrm{ACC}} + 0.047x_{\mathrm{HRR}} + 1.4238, \tag{1}$$

where x_{ACC} denotes the vector magnitude of the tri-axial acceleration signals and x_{HRR} denotes HR reserve, which depends on the heart's ability to increase heart rate during physical activity.

To eliminate the gravitational acceleration component, the tri-axial acceleration signals are high-pass filtered with a cut-off frequency of 0.7 Hz (Oshima *et al* 2010). Then, the vector magnitude is computed and averaged within 1 min intervals to yield x_{ACC} (Nakanishi *et al* 2018).

The HR reserve x_{HRR} is defined as follows,

$$x_{\mathrm{HRR}} = \frac{x_{\mathrm{HR},a} - x_{\mathrm{HR},r}}{x_{\mathrm{HR},m} - x_{\mathrm{HR},r}} \cdot 100, \tag{2}$$

where $x_{\mathrm{HR},a}$ is the mean HR in 1 min intervals and $x_{\mathrm{HR},r}$ is the mean of the 5 min HR during daytime sedentary activities, determined as the mean amplitude deviation (MAD) of the tri-axial, unfiltered acceleration signals within the range of 3–15 milligravity. The measure $x_{\mathrm{HR},m}$ is the maximum heart rate determined using the standard formula 220 minus age.

A trigger is detected if the mean MET, computed for 1 min intervals with non-AF rhythm, exceeds 5 METs. Considering that most patients were elderly, the threshold for detecting physical exertion is adjusted to 5 METs instead of 6 METs typically used to characterize vigorous activity in a younger population (Patel *et al* 2019).

2.3.2. Psychophysiological stress

During psychophysiological stress, the body releases stress hormones thereby contributing to elevated HR and intensified cardiac contractions, potentially leading to the occurrence of AF episodes (Leo *et al* 2023). Detection of psychophysiological stress relies on the assumption that a sudden elevation in HR, not attributable to notable physical activity or arrhythmia, is indicative of a stress-inducing event.

A trigger is detected when the elevation in HR exceeds 15 beats per minute within a 1 min interval (Brouwer and Hogervorst 2014), provided that no physical activity is present and no trigger has been detected during the preceding 4 h. Physical activity is considered absent when both the average MAD of the 5 min interval before and the analyzed 1 min interval remain below 22.5 mg, a level that indicates sedentary behavior such as sitting and standing still (Vähä-Ypyä *et al* 2018). To reduce the impact of outliers, the elevation is not determined directly from the HR series but by computing the difference between end and onset of a first-degree polynomial fitted to the HR series in the 1 min interval.

2.3.3. Lying on the left side

The left lateral lying position has been self-reported as a trigger of AF episodes (Groh *et al* 2019, Gottlieb *et al* 2021b). This finding can be explained by the left lateral position exerting heightened pressure on the walls of

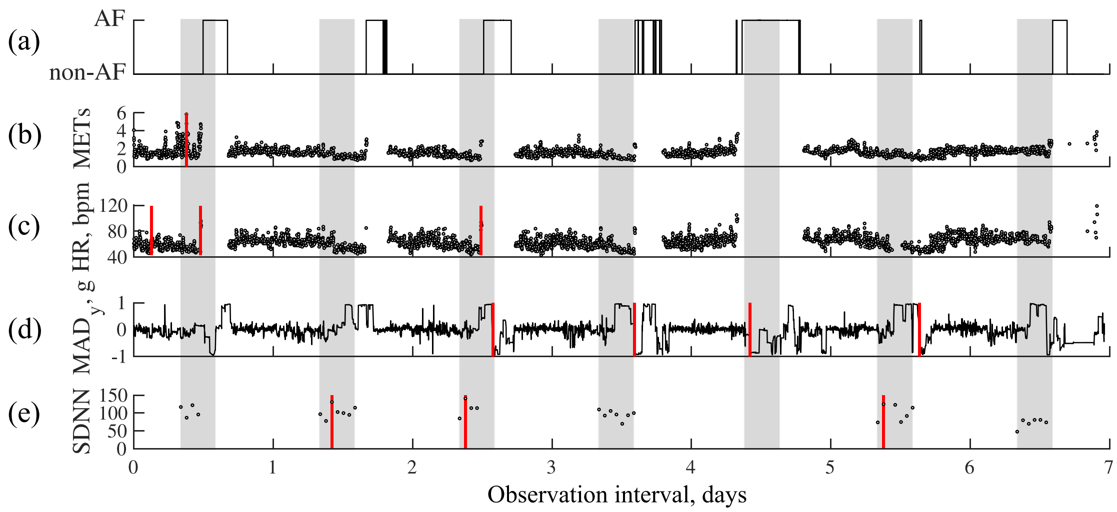

Figure 2. An example of (a) annotated AF episodes, and the different time series of parameter values and detected triggers related to (b) physical exertion, (c) psychophysiological stress, (d) left lateral lying position, and (e) sleep disturbances. The occurrence times of the triggers are indicated with red vertical lines. The nighttime intervals, spanning from midnight to 7:00, are displayed in grey.

the atrial and pulmonary vein, thereby functioning as a proarrhythmic factor (Chang *et al* 2007, Gottlieb *et al* 2021a, 2023).

A trigger is detected when the acceleration signal of the mediolateral axis (MAD_y), i.e. the signal best reflecting the left lateral lying position, remains below −600 mg for at least 1 h and no trigger has been detected during the preceding 4 h. Given that changes in lying position occur multiple times during the night, only the first detected trigger is considered for the preceding 4 h.

2.3.4. Sleep disorders

Sleep disorders, particularly obstructive sleep apnea, have been identified as potential triggers of AF (Mehra *et al* 2022, Wong *et al* 2024). Given that episodes of obstructive sleep apnea are often accompanied with cyclic variations in HR, certain HR variability indices are well-suited for detecting such episodes (Roche *et al* 1999). In this study, nocturnal alterations in HR are explored using the standard deviation of normal-to-normal RR intervals (SDNN), serving as an indicator of the dominant component of sympathetic and vagal activity (Malik and Camm 2004).

Before SDNN is computed, the RR interval series is corrected with respect to missed beats, false detections, and ectopic beats, using the algorithm described in Lipponen and Tarvainen (2019). False detections are eliminated, and, for a missed beat, a new beat is inserted to divide the prolonged RR interval into two RR intervals of the same length. Ectopic beats are handled by interpolation of the adjacent RR intervals.

To detect sleep disorders, the nighttime interval from midnight to 7:00 was analyzed, computing SDNN within 1 h increments. A threshold of 116 ms is employed to determine the large variations in HR based on the SDNN (Roche *et al* 1999). When the SDNN exceeds the threshold in a 1 h interval, the onset of the interval is taken as the occurrence time of the trigger.

2.4. Trigger example

An example of the four series of parameter values, the detected triggers, and the annotated AF episodes, is presented in figure 2. For this particular patient, lying on the left side seems to be linked with AF episode occurrence. However, this may not be true for other patients as different patients may have different types of trigger.

2.5. Quantifying the relation between a potential trigger and the occurrence of AF episodes

The assessment of the relation between a potential trigger and the occurrence of AF episodes is based on AF burden, defined as the ratio of time spent in AF to the total duration of the analysis time interval T. The relational strength γ relies on the assumption that the post-trigger AF burden $B_{1,n}$ of the nth trigger exceeds

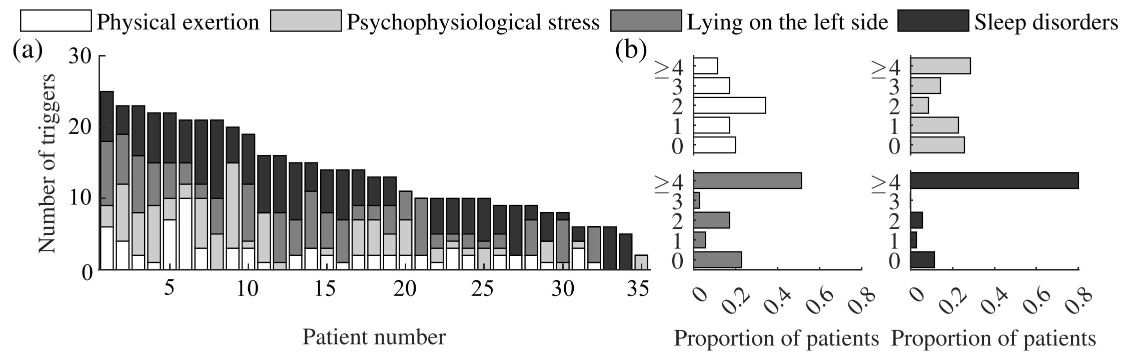

Figure 3. (a) Stacked diagrams of the number of triggers detected in each patient, with patients ranked in descending order based on the total number of detected triggers. (b) The proportion of patients with a particular number of triggers detected over the observation interval.

the pre-trigger AF burden $B_{0,n}$ (Pluščiauskaitė *et al* 2024):

$$\gamma = \sum_{n=1}^{N_t} \frac{B_{1,n}}{1 + B_{0,n}} H(B_{1,n} - B_{0,n}), \tag{3}$$

where N_t denotes the number of triggers during the observation interval. The Heaviside step function $H(\cdot)$ excludes instances when the pre-trigger burden is larger than the post-trigger burden.

The analysis time interval T, used to compute $B_{1,n}$ and $B_{0,n}$, is set to the anticipated duration of the trigger effect, here taken to be 4 h (Marcus *et al* 2021). Depending on whether γ relates to detector-based or annotated AF episodes, it is denoted $\gamma_{\mathtt{d}}$ and $\gamma_{\mathtt{a}}$, respectively.

To assess γ unrelated to the trigger, a control $\gamma_{\mathtt{c}}$ is computed using randomly placed control triggers. The number of control triggers used for computing $\gamma_{\mathtt{c}}$ is identical to the number of detected triggers.

2.6. Statistical analysis

Normality is assessed using the Shapiro–Wilk test, and, given the non-normal distribution, boxplots are employed to summarize the results. The Wilcoxon signed-rank test is used to compute p-values for assessment of differences between dependent groups, while the Mann–Whitney U test is used for assessment of differences between independent groups.

Scatter plots are used to show the degree of association between γ, computed for each trigger type, either for annotated or detector-based AF episodes. The association is assessed using linear regression, and the results are presented using the Spearman correlation coefficient.

3. Results

Figure 3(a) shows the number of each trigger type detected in each patient. At least one trigger of physical exertion, psychophysiological stress, lying on the left side, and sleep disorders was detected in 80%, 74%, 71%, and 89% of the patients, respectively. A median of 2 (IQR 1–3), 2 (1–5), 4 (1–6), and 5 (4–7) triggers were detected for physical exertion, psychophysiological stress, lying on the left side, and sleep disorders, respectively (figure 3(b)); the related interquartile range is given within the parenthesis.

Figure 4 shows $\gamma_{\mathtt{c}}$ as a function of the number of triggers for different numbers of random initializations. In the computation of $\gamma_{\mathtt{c}}$, N_t uniformly distributed timestamps were generated in the observation interval. To ensure robustness of $\gamma_{\mathtt{c}}$, a median of 100 random initializations was used.

Figure 5 shows $\gamma_{\mathtt{d}}$ for detected triggers and $\gamma_{\mathtt{c}}$ for control triggers in patients with at least one trigger. The results show that, for some patients, $\gamma_{\mathtt{d}}$ increases substantially for all four trigger types relative to $\gamma_{\mathtt{c}}$. Overall, physical exertion emerged as the most significant trigger, associated with the largest increase in $\gamma_{\mathtt{d}}$ across the largest number of patients ($p < 0.01$); no significant difference was observed between $\gamma_{\mathtt{d}}$ and $\gamma_{\mathtt{c}}$ for psychophysiological stress and sleep disorders. Additionally, no significant difference in $\gamma_{\mathtt{d}}$ was found between females and males, with p-values of 0.06, 0.34, 0.49, and 0.66 for physical exertion, psychophysiological stress, lying on the left side, and sleep disturbances, respectively.

Figure 6 shows that $\gamma_{\mathtt{a}}$ is moderately correlated with $\gamma_{\mathtt{d}}$, with the correlation coefficients $r = 0.66$ and $r = 0.62$ for ECG- and PPG-based AF detection, respectively.

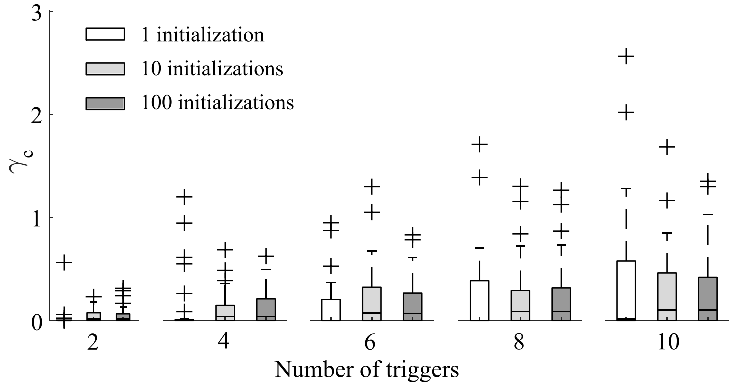

Figure 4. Control relational strength γ_c as a function of the number of triggers for different numbers of random initialization.

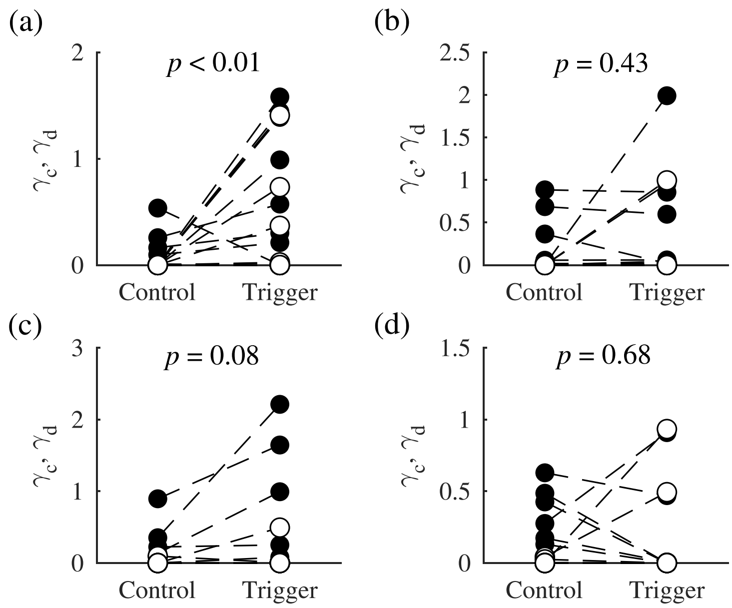

Figure 5. The relational strengths γ_c and γ_d, obtained using control triggers and detector-based triggers, respectively, computed for each patient and different types of trigger: (a) physical exertion, (b) psychophysiological stress, (c) lying on the left side, and (d) sleep disorders. Females are represented by white circles.

4. Discussion

An important finding of the present study is a substantial increase in γ_d relative to γ_c in certain patients. This finding is consistent with those of questionnaire-based studies (Hansson *et al* 2004, Groh *et al* 2019), which indicate the absence of a universal AF trigger. On the contrary, depending on the presence of other factors that increase the propensity for AF (Nattel and Dobrev 2016), triggers will induce AF in certain patients. To evaluate the temporal relation between detected triggers and AF occurrence, one might assume that the number of episodes would increase after the trigger. However, the number of episodes in pre- and post-trigger intervals was found to be similar in our study. Therefore, employing a cumulative principle as the one in the definition of γ, might prove to be more effective in detecting triggers.

Evidence suggests a J-shaped relation between physical activity and the risk of AF, indicating that light and moderate physical activity can reduce the risk of AF, while both inactivity and vigorous physical activity can elevate the risk of AF (Guasch and Mont 2017). However, the exact mechanisms through which vigorous physical activity may trigger AF are not known. One plausible explanation involves the interplay between the autonomic nervous system and atrial remodeling, leading to AF episodes (D'Ascenzi *et al* 2015). Regarding vagally induced AF, patients who engage in regular physical activity tend to experience AF episodes more frequently than their sedentary counterparts (Mont *et al* 2002). Furthermore, increased vagal activity is associated with a shortened atrial refractory period, facilitating re-entry and potentially triggering AF (Morseth *et al* 2018).

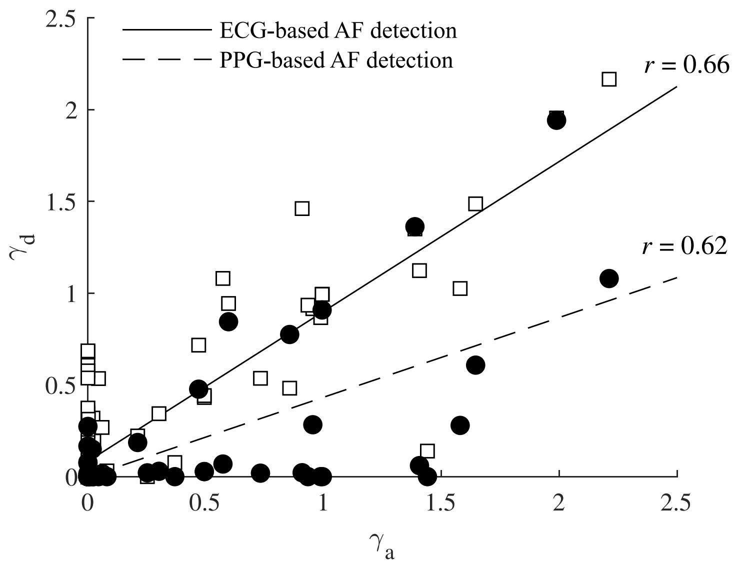

Figure 6. Association between γ_a, obtained using annotated AF episodes, and γ_d, obtained using detector-based AF episodes, for pooled data encompassing all four types of trigger. Bright squares and dark circles represent ECG- and PPG-based detection of AF episodes, respectively.

An increasing number of studies are investigating the utility of MET units as a measure for determining thresholds in classifying the intensity of physical activity (Mansoubi *et al* 2015, Mendes *et al* 2018, Nakanishi *et al* 2018). However, the majority of these studies have predominantly focused on young or middle-aged adults, while less so on the elderly. Considering the variable effort levels required by patients of different age groups to execute identical activities, discernible differences in energy expenditure become apparent (Nagayoshi *et al* 2019). Relying solely on estimation of MET from acceleration and HR data may inadequately capture the true energy expenditure, potentially resulting in underestimation of MET (Byrne *et al* 2005). To account for age-related differences in the present study population, the threshold designating physical exertion was set to 5 METs instead of the conventional 6 METs used for identifying vigorous activity. This adjustment accommodates activities such as stair climbing, brisk walking, and table tennis (Ainsworth *et al* 2011).

Psychophysiological stress has an adverse impact on the cardiac system, potentially elevating the risk of developing AF (Leo *et al* 2023). Their potential role as triggers of AF is indicated by findings from laboratory-induced stress tests and several observational studies (Severino *et al* 2019, Leo *et al* 2023). During stress and negative emotions, the body releases stress hormones, including adrenaline, noradrenaline, and cortisol. These hormones impact blood flow by triggering mechanisms such as elevated HR and increased blood pressure. Moreover, stress exerts direct effects on the heart, inducing alterations in cardiac electrical activity, which in turn may contribute to the initiation and perpetuation of AF. The interplay between stress, physiological responses, and cardiac electrophysiology underscores the multifaceted nature of the relation between psychophysiological stress and AF, warranting further investigation to elucidate the underlying mechanisms and targeted interventions.

Patients frequently report that a left lateral body position triggers AF episodes (Groh *et al* 2019). Twenty-two percent of the patients noted a particular body posture that induced their AF symptoms. Among those, the left lateral position has been identified as the triggering posture in 57% of all cases (Gottlieb *et al* 2021b). The AF triggering mechanism of a left lateral body position can be explained by a heightened stretch of the pulmonary veins, which are known to be proarrhythmic for AF. Changing from a supine to a left lateral position causes the heart to shift in an anterior-left lateral direction within the thorax. This alteration leads to an increase in left atrial volume and an elevation in local wall stress in the pulmonary vein regions (Gottlieb *et al* 2021a).

The relational strength in individual patients has been assessed utilizing an approach well-suited for non-stationary and binary data (Pluščiauskaitė *et al* 2024). The approach builds on a cumulative principle, as there is no basis to assume that the trigger influences AF burden consistently. It is more likely that the trigger sporadically initiates AF due to the interplay of various factors that augment the propensity for AF (Vincenti *et al* 2006, Nattel and Dobrev 2016, Severino *et al* 2019). Therefore, γ_d should be interpreted in light of the number of triggers detected. For a single trigger, $\gamma_d = 1$ indicates a moderate strength, signifying a scenario in which AF is initiated shortly after a trigger and persists throughout the analysis time interval, with no pre-trigger AF burden. In cases where both the pre- and post-trigger burdens are larger than 0, γ_d falls within the interval $0.5 \leqslant \gamma_d < 1$, indicating a weak relational strength. Conversely, when both the pre- and post-trigger burdens approach zero, γ_d is less than 0.5, suggesting a very weak relational strength. To establish a strong relational strength, at least two triggers must be detected.

The choice of the analysis time interval T, employed to compute both pre- and post-trigger burdens, is another influential determinant for γ_d which has to take the anticipated duration of the trigger effect into account. In this study, T was set to 4 h for all trigger types; nevertheless, the choice of T deserves further attention. A too brief interval may only capture a partial effect of the trigger, while a too long interval may include intervals beyond the trigger effect. Additionally, it is important to consider the time lag between the trigger and the onset of an AF episode. For instance, the influence of alcohol consumption on AF occurrence may persist for up to 12 h (Marcus *et al* 2021), with the highest prevalence of AF episodes occurring at 4 h following the onset of alcohol consumption. However, the lasting effect of the types of trigger explored in this study is not as clear.

In this study, an ECG patch attached to the chest was employed to acquire physiological signals. While wrist-worn PPG-based devices have attracted increasing attention for continuous monitoring in everyday settings, their suitability for trigger detection remains unclear. This is primarily due to two factors: lack of a stable reference point for accelerations and lower accuracy in HR estimation. Commonly, the mean absolute percentage error of the estimated HR from a PPG is 5%–20% (Bent *et al* 2020, Düking *et al* 2020, Germini *et al* 2022). Furthermore, the error increases by up to 30% during high-intensity physical activity compared to resting states. Such large errors pose a limitation to detecting physical exertion, psychophysiological stress, or sleep disturbances using HR variability analysis. An additional challenge is the detection of lying on the left side based on wrist-derived acceleration signals since sleep posture varies considerably between individuals, and behavior is less controlled during sleep. Unsurprisingly, the wrist location was found to be the least reliable for accelerometer-based detection of lying posture (Alinia *et al* 2020).

PPG-based AF detection in everyday settings is affected by other factors, such as non-wear time and motion artifacts (Inui *et al* 2020, Pluščiauskaitė *et al* 2023). In our study, AF burden, determined from AF episodes acquired by the PPG-based detector, exhibited a reduction of approximately 70% when compared to annotated episodes. This reduction was primarily attributed to the exclusion of a substantial portion of the PPG signal due to poor quality and non-wear time. These findings are consistent with those reported in Zhu *et al* (2021), where a coverage rate of 52% was achieved, although the patients were encouraged to wear a device overnight. This reduction in estimated AF burden is important, particularly in light of the fact that trigger-induced increments in AF burden are typically on the order of a few percentage (Voskoboinik *et al* 2020).

Sleep disorders, such as poor sleep quality, snoring, and obstructive sleep apnea, are frequently associated with AF (Genuardi *et al* 2019, Mehra and Marcus 2019, Mehra *et al* 2022). Research has shown a 15% higher risk of experiencing an AF episode following a night of poor sleep (Wong *et al* 2024). Additionally, prolonged instances of poor sleep have been associated with longer AF episodes (Wong *et al* 2024). Since most adverse health conditions tend to decrease HR variability (Kleiger *et al* 2005), SDNN appears to be robust against false detections of sleep disturbances. This can be substantiated by the findings in Roche *et al* (1999), where a nocturnal SDNN exceeding 116 ms detects sleep apnea with 90% specificity. However, dedicated wearable devices for sleep monitoring may offer greater accuracy in detecting sleep disturbances. For example, commercial sleep analyzers equipped with pneumatic and acoustic sensors can be used to identify the onset and end of sleep and detect episodes of snoring and sleep apnea (Edouard *et al* 2021).

Triggers may alter the physiological systems, for example, the autonomic nervous system, and, in this way, contribute to AF (Chen *et al* 2014, Rebecchi *et al* 2021, Joglar *et al* 2023). The autonomic activation influences the intracellular calcium dynamics, leading to a reduction in action potential duration and refractoriness which in turn may result in ectopic firing in atrial muscles surrounding the pulmonary veins (Kaakeh *et al* 2012). A noteworthy observation is that AF patients without structural heart disease tend to exhibit an increase in vagal tone before AF onset. Conversely, patients with structural heart disease have an increased sympathetic tone before AF onset (Olshansky 2005). The alterations in the autonomic nervous system can be studied using HR variability indices, potentially enhancing understanding of the processes that contribute to the initiation of AF.

At an early stage, we explored alterations in the autonomic nervous system using the widely adopted HR variability index, the low frequencies/high frequency ratio (LF/HF), serving as an indicator of the dominant component of sympathetic and vagal activity (Malik and Camm 2004). However, no difference was observed between pre- and post-trigger intervals in LF/HF. This outcome was likely influenced by the collection of data during unrestricted daily activities, leading to ECG signals of lower quality due to motion artifacts and noise. Since physical activity has an impact on the autonomic nervous system (Bishop 2004), it becomes challenging to accurately assess its relation to triggers during daily activities.

5. Limitations and future work

Within the initial cohort of patients diagnosed with paroxysmal AF, merely 24% encountered at least one AF episode throughout the one-week observation interval. Consequently, the results may be influenced by individual variation. Moreover, a relatively low AF burden among those who had AF episodes influenced the relational strength γ, being less sensitive to lower AF burden (Pluščiauskaitė *et al* 2024).

Most patients (74%) were administered with beta-blockers, which block the release of the stress hormone adrenaline and thus reduce HR. Since HR is directly involved in detecting physical exertion and psychophysiological stress, this may have led to fewer detected triggers.

The simultaneous occurrence of different types of trigger and their possible interaction was not taken into consideration. Assessing interaction is a complex task requiring more knowledge about the duration of the effect of each type of trigger. One solution is to group types of trigger based on the activated components of the autonomic nervous system (Groh *et al* 2019). While physical exertion and psychophysiological stress activate the sympathetic nervous system, the effect of lying on the left side on the autonomic nervous system is unknown.

The four types of trigger were chosen based on their feasibility for detection in physiological signals. In questionnaire-based studies, alcohol consumption, dehydration, large meals, and cold food have also been suggested as triggers of AF (Hansson *et al* 2004, Groh *et al* 2019), however, these triggers may not be easily detected in physiological signals.

Alcohol may have the strongest effect on AF occurrence, and, therefore, may act as a confounder or effect modifier of other triggers. Although acute alcohol intoxication typically causes temporary ECG changes, such as P-wave prolongation, QTc prolongation, T-wave abnormalities, and QRS complex prolongation (Raheja *et al* 2018), these changes can also result from other conditions, such as the use of certain medications or electrolyte imbalances. Therefore, information on alcohol consumption is usually obtained through questionnaires or ethanol detectors (Marcus *et al* 2021). In this study, the effect of alcohol on other AF triggers was not explored. However, it constitutes a challenging future research topic, particularly when analyzing the intermediate processes from the initial trigger to the occurrence of an AF episode.

Triggers in females and males is yet another interesting research question to explore, but so far such data are lacking. In a questionnaire-based study (Groh *et al* 2019), females were 2–3 times more likely to report lack of sleep and lying on the left side as trigger. In the present study, the number of triggers was similar in both sexes, i.e. lying on the left side was detected in 14 females and 12 males, sleep disturbances in 13 females and 14 males, physical exertion in 14 females and 12 males, and only psychophysiological stress was more common among males (14 versus 9). Given that differences may exist between males and females how triggers are experienced (Winborn *et al* 1988, Deng *et al* 2016), physiological signal-based detection of triggers may provide a more accurate assessment compared to relying solely on self-reported data.

This study outlines the principles of trigger detection in physiological signals but does not address the issue of missed and falsely detected triggers. This is due to several reasons, primarily the fact that the data were collected in the patients' homes. The occurrence times of potential triggers can be gathered through mobile apps or questionnaires, but both methods have notable limitations. Triggers are self-reported, leading to bias and a time delay between the actual event and when it is logged. The use of specific sensors, such as ethanol detectors, could shorten such delays for certain triggers. For example, self-reported alcohol consumption closely matched the results obtained from transdermal alcohol sensors (Marcus *et al* 2021). However, not all triggers can be detected using sensors. Validating physical exertion or psychophysiological stress is even more challenging because these triggers are subjective and therefore may differ from the effects observed on physiological signals. Meanwhile, sleep disturbances can be detected in sleep laboratories or using a sleeping mat, which offers a cheaper but less reliable alternative.

6. Conclusions

The results show an increase in the relational strength between detected triggers and the occurrence of AF episodes for some patients, particularly related to physical exertion and lying on the left side. A moderate correlation in relational strength was found when the detector-based AF episodes were compared to the annotated AF episodes. The proposed approach has the potential to facilitate the implementation of longitudinal studies, allowing for less-biased detection of AF triggers without the need for questionnaires.

Data availability statement

The long-term physiological signal database of paroxysamal atrial fibrillation patients is currently is publicly available through open-access portal Zenodo: https://zenodo.org/records/11242869.

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