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Heart rate variability biofeedback in a global study of the most common coherence frequencies and the impact of emotional states

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This global study analyzed data from the largest dataset ever studied in the Heart Rate Variability (HRV) biofeedback field, comprising 1.8 million user sessions collected from users of a mobile app during 2019 and 2020. We focused on HRV Coherence, which is linked to improved emotional stability and cognitive function. Positive emotions reported by users were associated with higher Coherence scores and more stable HRV frequencies. In contrast, negative emotions exhibited lower scores and more dispersed frequency distributions. The most common frequency associated with Coherence was identified at 0.10 Hz. However, many users with the highest levels of Coherence fell within a lower range from 0.04 to 0.10 Hz. Most users exhibited high stability (standard deviation < 0.012 Hz) in their coherence frequencies from session to session, and their stability within a given session increased with increasing Coherence. The insights gained from this extensive dataset suggest that by instructing users to breathe deeper and slower and find a rhythm that's comfortable, they naturally find their unique resonant frequency. The findings provide a strong foundation for future research and the development of targeted interventions aimed at enhancing emotional and physiological well-being through HRV biofeedback and coherence practices.

Keywords Heart rate variability (HRV), Heart-rhythm coherence, Autonomic nervous system (ANS), Emotional states, Biofeedback, Resonant frequency breathing

Heart rate variability (HRV) biofeedback has emerged as a powerful tool for improving physiological and psychological well-being. Two prominent approaches in this field are the HeartMath self-regulation techniques combined with real-time HRV coherence assessment and feedback technologies and the resonant frequency breathing approach. Both methods aim to enhance aspects of HRV, but they differ in their specific focus and implementation[1–7]. Both approaches have demonstrated numerous benefits, including reduced stress, and enhanced physiological function. They share a number of common outcomes such as increased HRV, improved autonomic function, lower blood pressure and better overall well-being[2–4,6,8–15].

The research on resonant frequency breathing often emphasizes its use in clinical settings, particularly for treating various disorders and health conditions[1,16]. This approach focuses on identifying and practicing breathing at an individual's unique resonant frequency which results in the largest peak-to-trough amplitude in the HRV waveform. This method aims to maximize efferent vagal modulation of the heart rhythm by increasing respiratory sinus arrhythmia and breathing at a rhythm near the resonant frequency associated with the baroreflex system which is typically near 0.1 Hz, leading to increased HRV as compared to their resting state HRV. The typical protocol for this is to have participants breathe following a pacer for 2 min at each of 5 frequencies: (6.5, 6, 5.5, 5, 4.5 breaths/min) for adults and 6.5 to 9.5 breaths/min for children. The range of the inter-beat-intervals (IBI) is computed for each 2-minute record by looking at the peak-to-trough range (also called mean heart rate range). Once the breathing frequency resulting in the highest HRV amplitude is determined, the individual is instructed to breath at that rhythm, typically with various types of breath pacers set to that frequency[1]. For an in-depth discussion of the HRV frequency ranges and metrics see references[17,18].

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In contrast, the HeartMath HRV coherence model seems to have gained more traction in educational, workplace, and consumer markets due to its accessibility and broader focus on emotional self-regulation[2,3,6,19]. The HRV coherence model emphasizes the facilitation of self-regulation circuits and the neural interactions between the heart and brain and the importance of the neural patterns and their stability in the afferent cardiovascular neural inputs to the brain on emotional stability and cognitive functions[4,20]. Called the Heart-Rhythm Coherence hypothesis, it suggests that in addition to the amount of cardiovascular afferent vagal traffic to the brain, the patterns and stability of afferent inputs modulate cognitive performance and self-regulatory capacity over both short (within one or two cardiac cycles) and longer time scales (minutes)[4]. Mather and Thayer propose a compelling hypothesis suggesting that high-amplitude physiological oscillations have a causal impact on emotional well-being. Their theory posits that blood flow timing plays a crucial role in determining brain network structure and function, with slower frequency, high-amplitude oscillations in heart rate potentially improving brain network dynamics. This improvement is hypothesized to occur via fluctuations in blood flow, CO2 levels, and afferent inputs from breathing and the heart. These inputs are particularly likely to modulate activity in brain regions associated with emotion regulation, especially prefrontal regulatory areas that are highly sensitive to physiological oscillations[21]. Supporting this perspective, several studies have demonstrated that heartbeat-evoked potential amplitudes are significantly increased in numerous brain regions, including frontal areas, when participants engage in resonant frequency breathing or coherence techniques. This hypothesis provides a potential mechanistic explanation for the observed relationship HRV and emotional well-being, suggesting that interventions targeting physiological oscillations may have profound effects on brain function and emotional regulation[22,23].

The coherent state is characterized by a state specific higher amplitude, smooth, sine-wave-like pattern in the heart rhythm that emerges when synchronization and frequency entrainment occur between the heart rhythms, blood pressure, and respiration rhythms. This arises in the frequency range between 0.04 and 0.26 Hz of the HRV power spectrum, the coherence range[3] in which there is increased synchronization between the brain rhythm and the cardiac cycles[4]. The HRV coherence assessment algorithm is designed to detect the stability of the sine-wave like pattern in the heart rhythm independent of heart rate and the amplitude of the HRV rhythm. This is done so it will work with individuals across the age span as the amount of HRV decreases with age[24]. It also needs to detect any frequency within the coherence range which varies between individuals and can change within a session, tracking and feeding back a real-time coherence score. Therefore, the algorithm identifies the maximum peak in the 0.04–0.26 Hz range of the HRV power spectrum, calculates the integral in a window 0.030 Hz wide, centered on the highest peak in that region, then calculates the total power of the entire spectrum over a 64-second window that is updated every 5-seconds. The Coherence ratio (CR) is formulated as: the product of two ratios: CR = (Peak Power/Total power below the peak frequency)*(Peak Power/Total power above peak frequency) which is converted into a Coherence Score (CS) by taking the natural logarithm of CR + 1 which typically ranges between 0 and 8[2,4].

The HRV coherence feedback approach also includes the effect of emotional states on the heart rhythm. In earlier studies, we found that emotional states such as anger and appreciation are reflected differently in the patterns of the heart rhythm and in the power spectra[25]. In past studies[26,27] the focus was on the self-induction of various emotions and without any mention of altering one's breathing pattern. These studies found that participant's breathing rhythms co-varied with the emotions they were experiencing suggesting that the brain structures above the cardiorespiratory integration centers in the dorsal vagal complex involved in emotional processing and experience (amygdala, etc.) were unconsciously modifying the breathing rhythm, which is reflected in changes in the heart rhythm[4].

Importantly, these studies found that positive emotions, such as appreciation and compassion were typically associated with a highly ordered heart rhythm pattern, what is now called a coherent rhythm. Conversely, negative emotions, including anger, frustration, and anxiety, tend to produce irregular and erratic heart rhythm patterns. These incoherent patterns manifest as jagged, disorganized waveforms, suggesting a lack of synchronized activity in the higher brain structures and between the two branches of the autonomic nervous system[28]. Such states of incoherence have been linked to decreased physiological efficiency, increased energy expenditure, and potential long-term wear on bodily systems[4,29]. It has also been demonstrated that analysis of the HRV pattern alone can be used to quantify discrete emotional states with around 75% accuracy[30].

Therefore, the heart rhythm coherence feedback instruction and practice places greater emphasis on improving self-regulation and the importance of positive emotions as an important factor in sustaining heart rhythm coherence, which is also referred to as heart-brain coherence, heart coherence, cardiac coherence, vascular system resonance and entrainment[5].

The instructions in the Inner Balance app and on-line instructional videos for increasing heart rhythm coherence in stressful daily life contexts are given for two techniques. The Quick Coherence technique, which is designed to be used in-the-moment one may be experiencing stressful feelings has two steps. The first step is called Heart Focused Breathing: Focus your attention in the area of the heart. Imagine your breath is flowing in and out of your heart or chest area, breathing a little slower and deeper than usual. Find an easy rhythm that's comfortable. The second step is: As you continue heart-focused breathing, make a sincere attempt to experience a regenerative feeling such as appreciation or care for someone or something in your life. Try to re-experience the feeling you have for someone you love, a pet, a special place, an accomplishment, etc., or focus on a feeling of calm or ease. The second technique, the Heart Lock-In is a heart-focused meditation technique that is used in longer practice sessions. It shares the same first two steps but adds a third step which is to radiate that renewing feeling to yourself and others.

Previous experience has shown that with this approach individuals tend to naturally find their ideal breathing rhythm where the breathing rhythm, heart rhythm and beat-to-beat blood pressure rhythms frequency entrain at the resonant frequency of the heart-brain-lung system[25].

We have consistently found that with this approach and a little practice, most people are able to use the slower and deeper breathing rhythm to "jump-start" the shift into a more coherent rhythm and by then self-inducing a positive emotion, they tend to settle into their natural resonant frequency and sustain the coherent state for longer periods compared to only using a paced breathing approach[3]. This approach may be more accessible for everyday use as it does not require determining a specific breathing frequency. It also focuses on mental and emotional health and empowering individuals to self-regulate their thoughts, emotions and behaviors, which can have broader applications in daily life.

Many of the clinical, workplace and educational studies using HRV coherence feedback have included training in one or more self-regulation techniques designed to shift ones' physiology into a more coherent state when they are experiencing stress or wanting to enhance performance. Numerous studies that have used HRV coherence feedback technology to facilitate skill acquisition of self-regulation techniques have found significantly improved key markers of health, wellness and performance in many health-care, law enforcement, corporate, military and educational settings[4,11,12,31–50]. In a series of novel HRV biofeedback studies that combined the two HRV biofeedback approaches, researchers first determined participants' resonant frequency and then used the coherence score, which better reflects heart rhythm stability, as the feedback signal for home practice sessions. A study with younger and older adults found that after 5 weeks of daily HRV biofeedback practice that the intervention group had significantly increased cortical volume in left orbitofrontal cortex and increased low frequency HRV power compared to the control group. These changes were significantly correlated with reductions in mood disturbance suggesting that daily biofeedback sessions can increase resting state HRV and shape the brain circuits that help control HRV and regulate emotion[51]. Another study using the same intervention showed increased functional connectivity between the medial prefrontal cortex and left amygdala. This was associated with increased down-regulation of activity in somatosensory brain regions during an emotion regulation task, indicating that modulating heart rate oscillatory activity changes emotion network coordination in the brain[52]. A third study demonstrated that four weeks of practicing this intervention produced large effect size reductions in plasma amyloid-β levels in the intervention group, while levels increased in the control group[53].

The most recent study in this series examined the relationship between negative emotions and resting HRV. Pre-intervention assessments revealed significantly higher levels of negative emotions among participants with lower resting state vagally mediated HRV. Post-intervention analysis demonstrated that participants exhibiting greater increases in resting HRV also showed more substantial decreases in negative emotions. A mediation model incorporating all participants revealed that changes in resting HRV significantly mediated the relationship between training performance (i.e., coherent heart rate oscillation during practice sessions) and changes in negative emotion. Notably, this mediation effect was significantly moderated by condition and was only significant in the intervention group. These findings suggest that resting HRV changes mediated the mechanism by which coherent amplitude of heart rate oscillations reduced negative emotions, providing insight into the physiological pathways through which HRV coherence training may modulate emotional states[54].

This study analyzes the largest dataset ever studied in the HRV biofeedback field, comprising data from 1.8 million biofeedback sessions. It included a report of emotional states from a global population of individuals using the Inner Balance app (HeartMath, Boulder Creek, CA), who uploaded their session data to a server called HeartCloud during the years 2019 and 2020. Past studies of Heart Coherence have been smaller controlled experiments, but this study explores it in real-world settings and demonstrates its relevance in a broad global population. This study employed rigorous methodological approaches to ensure reproducibility and meaningful contribution to HRV-related interventions. These methods allowed us to uncover novel insights into HRV patterns associated with eight different user-reported emotional states. We identified the most prevalent coherence frequencies within this extensive dataset, examining their stability across various coherence levels and their modulation by emotional states. Our primary objective was to provide new perspectives on HRV coherence feedback practices and their potential implications for enhancing self-regulatory capacity, health, and well-being. The analysis focused on several key areas: (1) The identification of common coherence frequencies, (2) Assessment of frequency stability at different coherence levels, (3) Examination of emotional state influences on HRV patterns, and (4) Evaluation of the relationship between coherence levels and reported emotional states.

By analyzing this large-scale dataset, we aim to contribute to the growing body of knowledge on HRV biofeedback and its applications. Additionally, we explore the importance of contextual factors in interpreting various HRV measures, emphasizing the need for a nuanced understanding of HRV data in both research and clinical settings. This study's findings have potential implications for refining HRV biofeedback techniques, improving intervention strategies, and enhancing our understanding of the physiological correlates of emotional states. The results may inform future research directions and contribute to the development of more effective HRV-based interventions for promoting health and well-being.

Results

This study conducted a comprehensive analysis of Heart Rate Variability (HRV) data to explore the relationship between heart rhythm coherence frequencies, emotional states, and physiological regulation. The Inter-Beat Interval (IBI) time series and Power Spectral Density (PSD) analyses were utilized to demonstrate the relationship between coherence levels during HRV coherence feedback practice and HRV patterns. We compared average session coherence scores by emotion to highlight the impact of positive and negative emotional states on physiological coherence. Additionally, we analyzed various time and frequency domain HRV metrics across different coherence levels, revealing significant changes in autonomic nervous system activity at differing levels of heart rhythm coherence. The distribution of the most common coherence frequencies and their associated breathing cycle periods were examined to underscore the importance of specific frequencies in achieving higher levels of coherence. Finally, we assessed the variability in coherence frequencies by coherence level and emotion, emphasizing the increased stability associated with higher coherence levels and positive emotional states. These analyses collectively provide a more comprehensive understanding of the role of heart rhythm coherence feedback and emotional states on physiological rhythms, enhancing self-regulatory capacity and health outcomes.

Figure 1 illustrates the relationship between coherence levels and the patterns of the heart rhythm and their corresponding Power Spectral Density (PSD) for three different coherence levels: 0.7, 2.1, and 7.1. The top panel, with a coherence score of 0.7, shows a typical, irregular IBI pattern and a broad, low-amplitude PSD, indicating low coherence. The middle panel, with a coherence score of 2.1, displays a more regular IBI pattern and a more pronounced peak in the LF region of the PSD. The bottom panel, with a coherence score of 7.1, exhibits a highly regular, sinusoidal IBI pattern and a sharp, high-amplitude peak in the PSD around 0.1 Hz, reflecting high heart rhythm coherence. These results illustrate the relationship between coherence levels and the regularity of the heart rhythm patterns and spectral characteristics of the HRV.

To examine the relationship between emotional states and coherence levels during heart rhythm coherence feedback practice sessions, we analyzed the average coherence scores by the reported emotion for sessions conducted globally in 2019 and 2020. Figure 2(a) illustrates the average coherence scores by emotion for practice sessions uploaded to the server during this period, encompassing 1,884,216 user sessions of 3 to 15 min in duration. The sessions were conducted globally, with the following distribution: North America (1,059,630 sessions), Europe (552,209 sessions), Asia (64,354 sessions), Oceania (61,923 sessions), South America (20,143 sessions), Africa (8,146 sessions) and other regions (117,811 sessions). Figure 2(a) reveals that positive emotions such as "Excited," "Happy," and "Peaceful" are associated with higher average coherence scores (3.56, 3.49, and 3.40, respectively) compared to negative emotions like "Angry," "Anxious," "Bored," and "Sad" (2.57, 2.83, 2.81, and 2.75, respectively). The t-test results indicate that the differences in coherence scores between most emotions are statistically significant, with p-values of < 0.0001, except for "Content," which shows no significant difference (p-value: 0.28). Additionally, the overall comparison between positive and negative emotions shows a significant

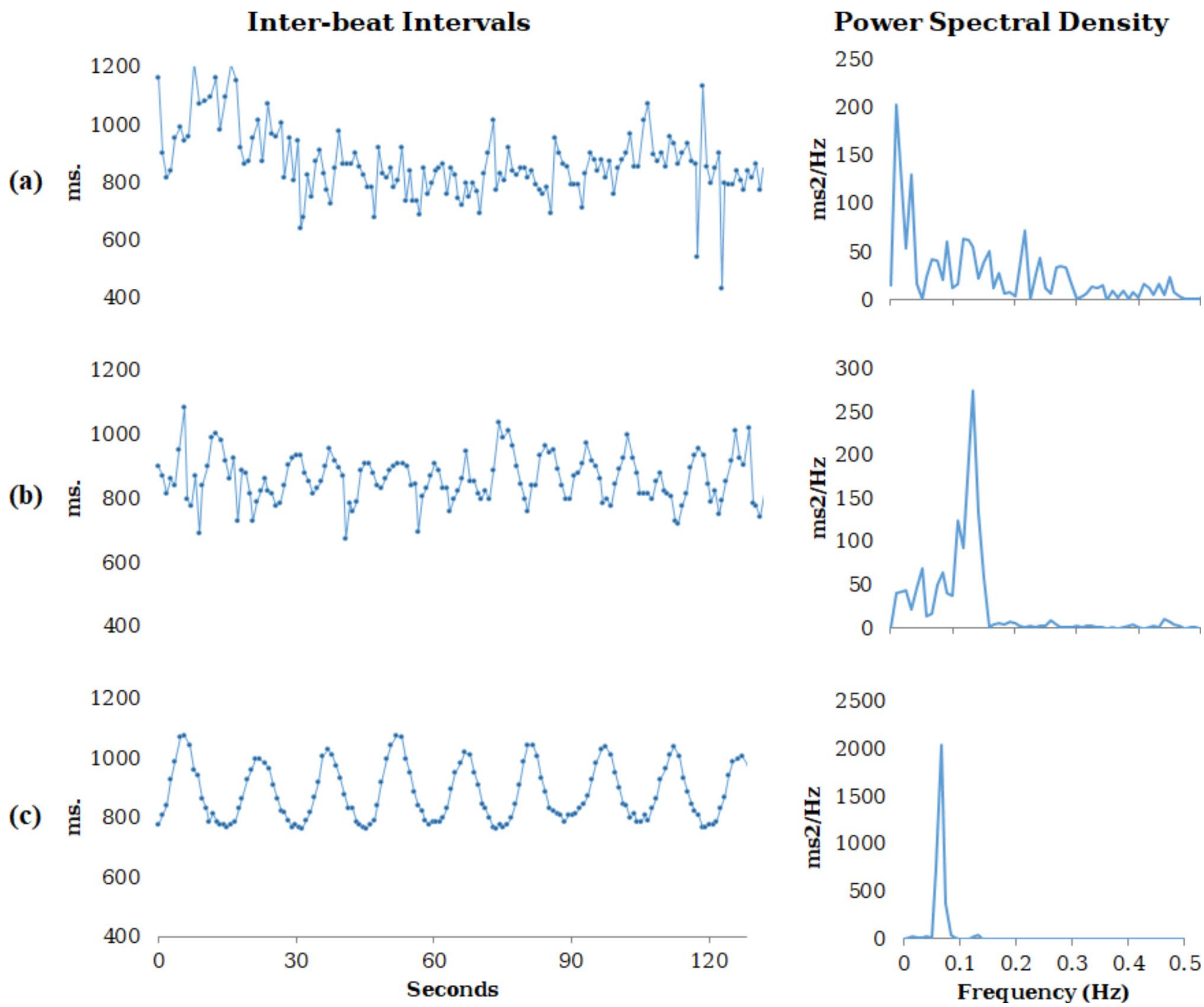

Fig. 1. Examples of Inter-Beat Interval (IBI) time series and Power Spectral Density (PSD) for coherence levels (**a**) 0.7, (**b**) 2.1, and (**c**) 7.1.

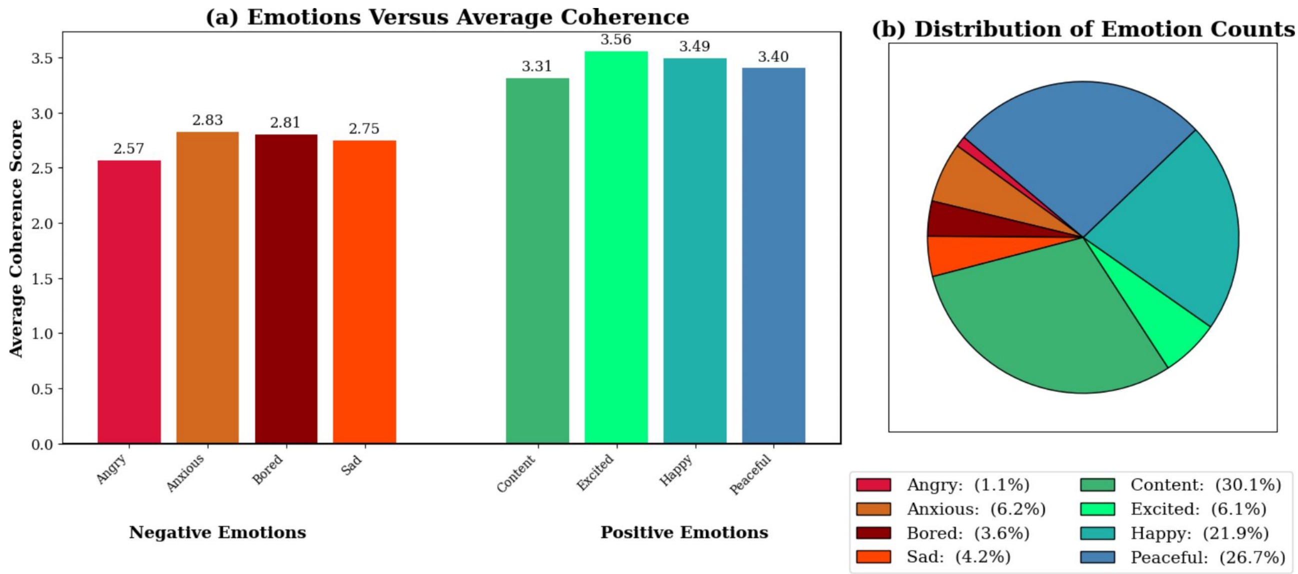

Fig. 2. (**a**) Average coherence summarized for the user-reported emotions (**b**) pie chart distribution of the reported emotions across all sessions.

difference in average coherence scores, with positive emotions yielding a higher average coherence score of 3.44 compared to 2.74 for negative emotions. The t-test conducted for the overall comparison between positive and negative emotions confirms this significant difference, with a t-statistic of -207.84 and a p-value of < 0.0001 which strongly suggests that positive emotional states are associated with achieving higher coherence levels during the feedback sessions.

To provide a visual representation of the distribution of emotion counts among the user sessions, we analyzed the frequency of reported emotions. Figure 2(b) provides a visual representation of the distribution of emotion counts among the user sessions. The pie chart shows that "Content" is the most frequently reported emotion after the completion of a session, accounting for 30.1% of all sessions, followed by "Peaceful" (26.7%), "Happy" (21.9%) and "Excited" (6.1%). Negative emotions such as "Anxious" (6.2%), "Bored" (3.6%), "Sad" (4.2%), and "Angry" (1.1%) make up a smaller portion of the overall distribution. This distribution indicates a predominance of positive emotional states among the users, which aligns with the higher average coherence scores observed for these emotions in Fig. 2(a). The relatively high proportion of "Content," "Peaceful," and "Happy" suggest that users are more likely to experience these positive states during the coherence sessions.

To investigate how different coherence levels impact various HRV metrics, we conducted a detailed ANOVA analysis of SDNN, Mean IBI, and natural logarithm of LF Power (LnLF), HF Power (LnHF), RMSSD (LnRMSSD), and LF/HF ratio (LnLF/HF), and the actual values are displayed in Fig. 3. Figure 3 shows the results of the analysis of HRV metrics by coherence levels, revealing significant differences across these metrics. For SDNN, there is a clear decreasing trend from the 0–1 level (108.92 ms) to the 3–4 level (88.63 ms), with a slight increase in the 5 + level (92.54 ms) which is due to the increased order in the distribution of the IBIs. Mean IBI, which is the inverse of heart rate, shows a gradual increase from the 0–1 level (850.35 ms) to the 4–5 level (882.65 ms), with a slight decrease in the 5 + level (881.06 ms). As expected, LF Power increases significantly from the 0–1 level (0.55 ms^2) to the 5 + level (0.77 ms^2), indicating an increase in the stability and amount of HRV. HF Power decreases from the 0–1 level (0.41 ms^2) to the 5 + level (0.13 ms^2) due to the respiratory rhythms being frequency entrained with the heart rhythm in the LF region of the power spectrum. For RMSSD, there is a decreasing trend from the 0–1 level (120 ms) to the 5 + level (80 ms), which would mistakenly be interpreted as reduced vagally-mediated HRV. However, this is not the case in this context as will be discussed in more detail in the discussion section. The LF/HF Ratio shows a substantial increase from the 0–1 level (6.43) to the 5 + level (23.60), which in this context was expected as LF power was significantly increased and is a signature of higher vagal activity and coherence levels.

ANOVA results confirm significant differences in all metrics ($p < 0.0001$), and post-hoc Tukey HSD (Honestly Significant Difference), analysis used after ANOVA to find means that are significantly different from each other, revealed that these differences are significant across most pairwise comparisons. For SDNN, the largest mean difference is observed between the 0–1 and 3–4 levels (-20.29 ms), while for Mean IBI, the largest difference is between the 0–1 and 3–4 levels (32.48 ms). LF Power shows the largest difference between the 0–1 and 5 + levels (0.22 ms^2) and HF Power also shows the largest difference between the 0–1 and 5 + levels (-0.28 ms^2). The LF/HF Ratio exhibits the most substantial difference between the 0–1 and 5 + levels (17.17), highlighting the pronounced increase in LF power in the higher coherence levels. Taken together, these findings suggest that higher coherence levels are associated with more stable and synchronized physiological states.

To understand the distribution of the naturally occurring coherence/resonance frequencies across the different levels of coherence, we analyzed the most common frequencies in the HRV spectrum among users' sessions. Figure 4 provides a comprehensive distribution of the most common coherence frequencies within

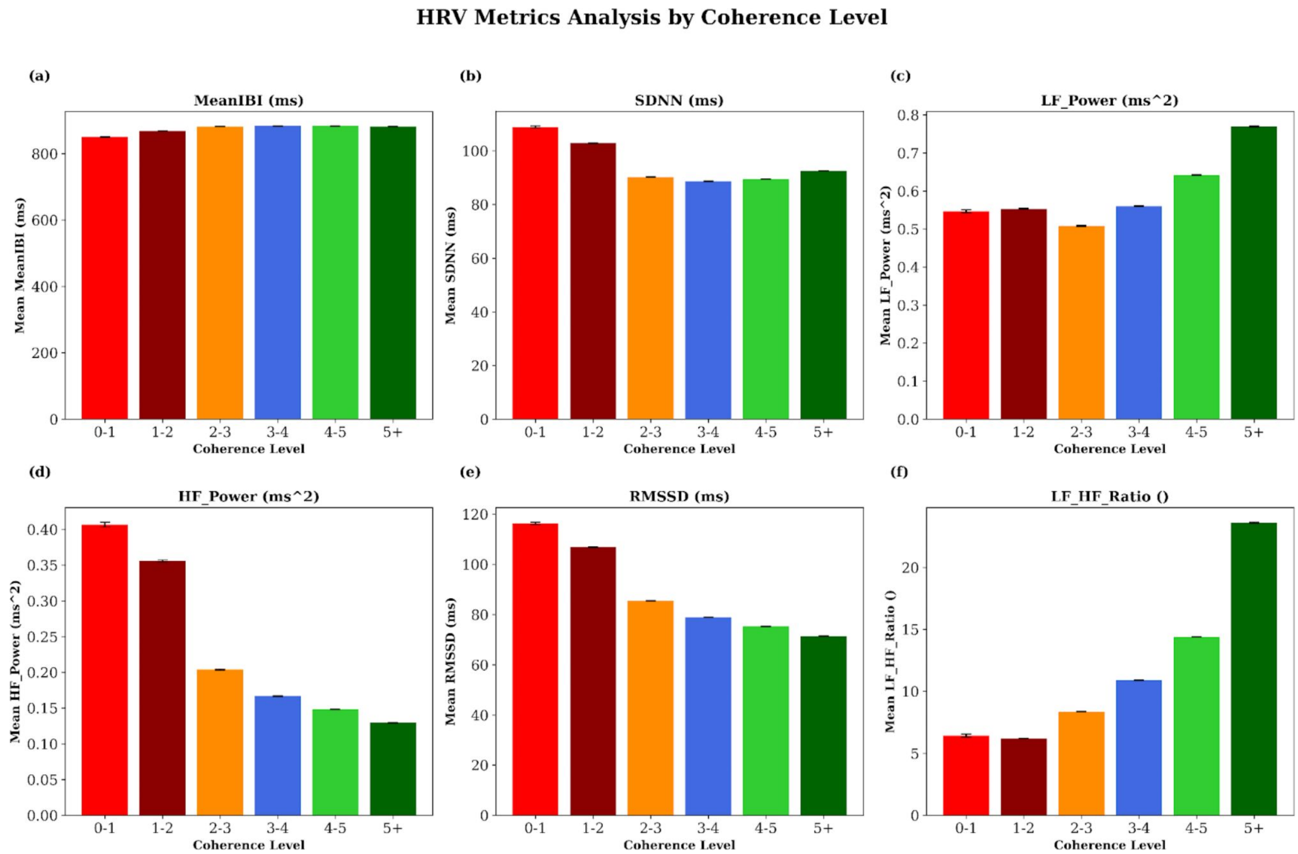

Fig. 3. Averages of various HRV metrics by sessions with different Coherence levels: (**a**) Mean IBI, (**b**) SDNN, (**c**) LF Power, (**d**) HF Power, (**e**) RMSSD, (**f**) LF/HF Ratio.

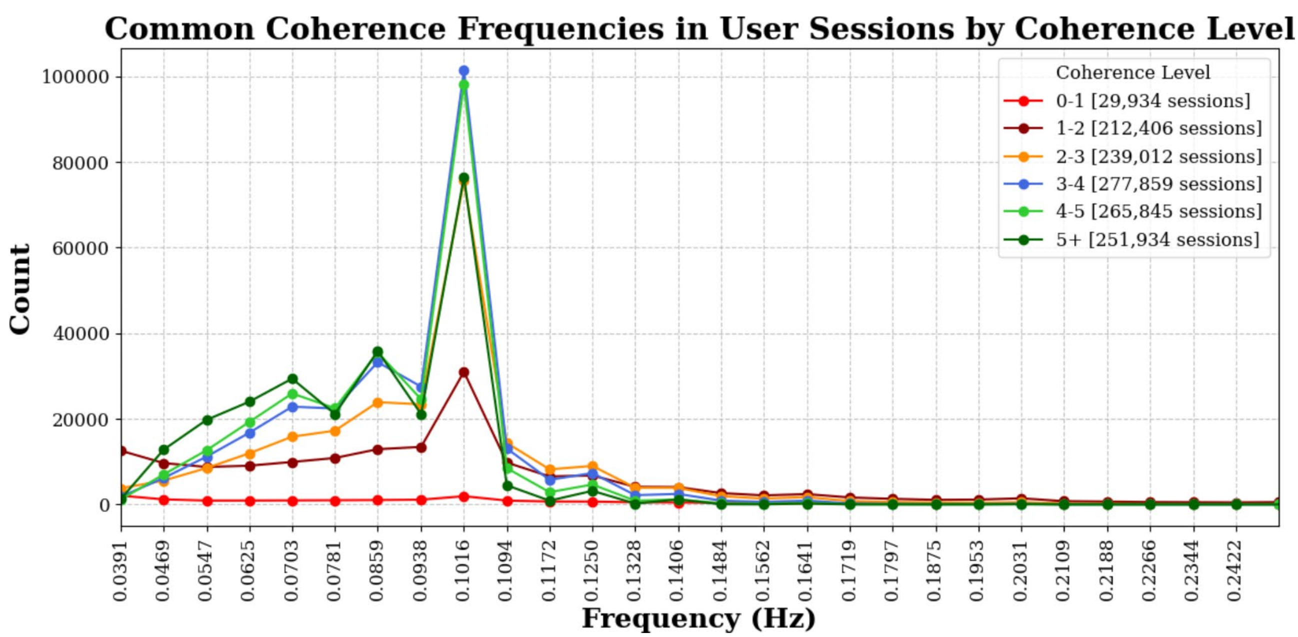

Fig. 4. Common coherence frequencies in user sessions by coherence level.

a session among user sessions, involving a pool of 68,301 users. The data illustrates that the most common frequency observed is 0.1016 Hz, with 384,596 sessions having this frequency. Additionally, Fig. 4 also categorizes these frequencies by coherence levels, where it is evident that higher coherence scores (4–5 and 5+) have a greater association with the 0.1016 Hz frequency. Conversely, lower coherence scores (0–1 and 1–2) exhibit a more dispersed frequency distribution, although the 1–2 level has the most sessions at 0.1016 Hz frequency. Surprisingly, a significant number of sessions had a coherence frequency below 0.1016 Hz, and the fraction of such sessions increased with coherence scores. At the highest coherence scores (5+), the number of sessions at 0.1016 Hz dropped relative to lower scores while the number of lower-frequency sessions continued to rise. A chi-squared test for independence further confirms that the association between coherence categories and frequency distributions is statistically significant, with a p-value of < 0.0001 indicating a strong dependence of frequency distributions on the coherence levels. These results imply that higher coherence levels are associated with a more stable and prevalent frequency, around 0.1016 Hz for the majority of individuals but for some at even lower frequencies, especially at the highest coherence scores.

To examine the relationship between HRV spectrum frequencies and average coherence scores, we analyzed the average coherence scores across the range of coherence/resonance frequencies. Figure 5 shows the average coherence scores across the range of frequencies in the HRV power spectrum. This analysis revealed that higher average coherence scores tend to be observed in the range of frequencies from 0.0469 to 0.1016 Hz. This is particularly evident at low frequencies around 0.0547 Hz, 0.0625 Hz, and 0.0703 Hz, with coherence scores of 4.06, 4.05, and 4.05, respectively. These frequencies exhibit higher scores compared to the 0.1016 Hz frequency, which has an average coherence score of 3.83. This suggests that while 0.1016 Hz is the most frequently observed coherence/resonant frequency, there is a broader range of coherent frequencies that are being experienced, from 0.0469 Hz to 0.1016 Hz. It is also consistent with the observation that a larger fraction of users experience frequencies below 0.1016 Hz at the highest coherence scores (5+). An ANOVA test further reinforces the finding that there are statistically significant differences in average coherence scores across different frequency bins, with an F-statistic of 6893.01 and a p-value of < 0.0001. The relatively high average coherence scores at these lower frequencies may indicate that these users are achieving a more stable and relaxed physiological state at these lower frequencies. This observation underscores the importance of exploring the full range of naturally occurring heart rhythm frequencies to optimize feedback approaches to facilitate self-regulation and enhance mental, emotional and physiological well-being.

To help visualize the inverse relationship between breathing cycles in seconds and HRV spectrum frequencies, we include Fig. 6 which shows the conversion between the breathing cycle period and coherence frequencies. The breathing cycle period for the most observed frequency, 0.1016 Hz, is approximately 9.84 s. Following this are the frequencies 0.0781 Hz and 0.0859 Hz, associated with breathing cycle periods of approximately 12.81 s and 11.64 s, respectively. Notably, higher coherence levels tend to cluster around these specific lower coherence frequencies, suggesting that these are also common naturally occurring resonant frequencies in many individuals.

To explore how different emotional states may influence the heart rhythm, we analyzed the distribution of the HRV frequencies by emotion. Figure 7 shows the distribution of the frequencies by emotion, revealing distinct patterns across different emotional states. Positive emotions such as "Peaceful," "Happy," "Excited," and "Content" show a pronounced peak around the 0.1016 Hz frequency, indicating a strong trend between positive

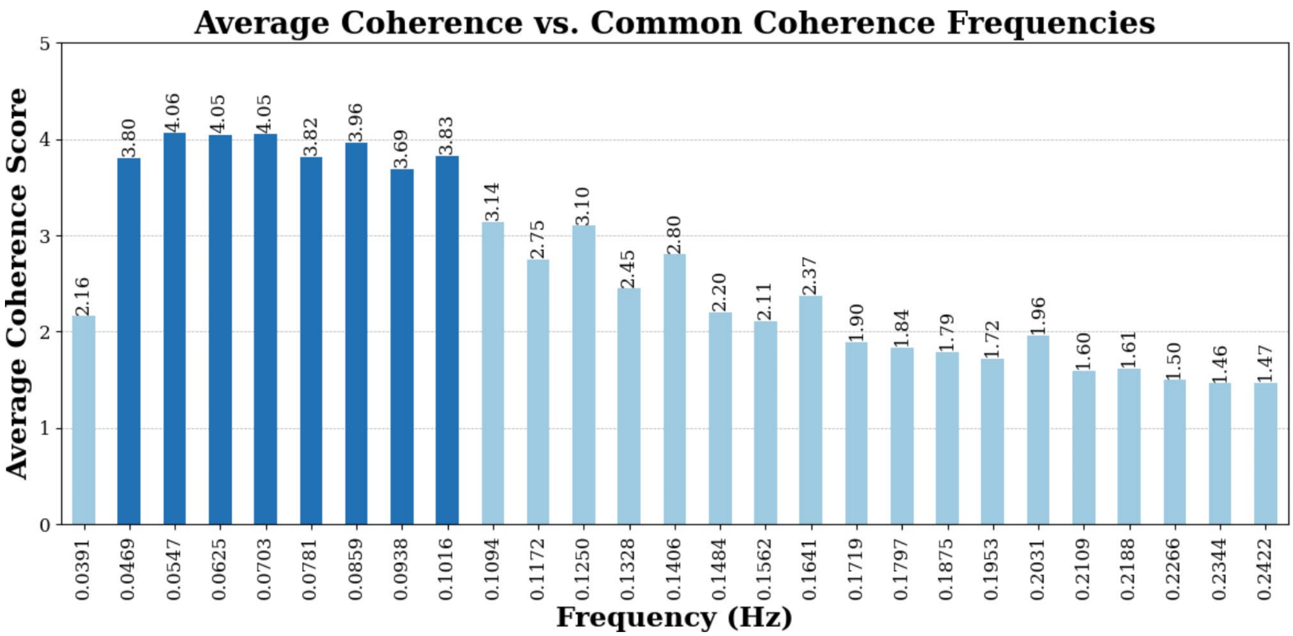

Fig. 5. Average coherence scores across common coherence frequencies. The darker blue bars indicate the highest coherence sores.

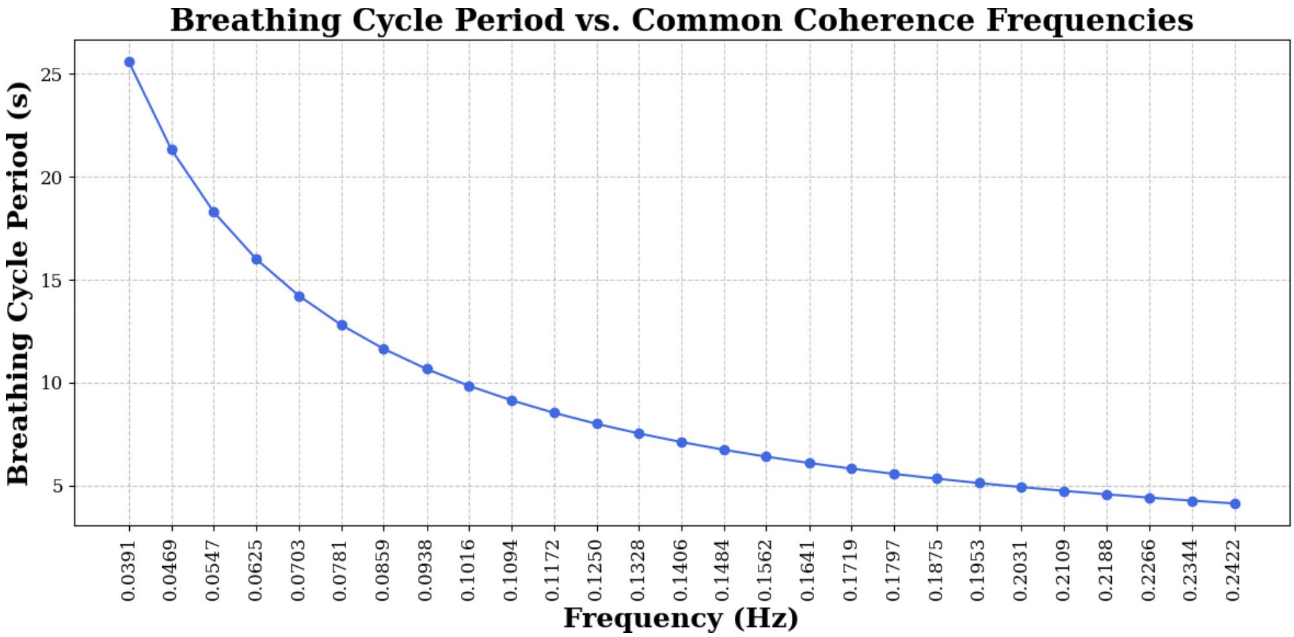

Fig. 6. Breathing cycle period vs heart rhythm coherence frequencies.

emotions and this frequency. In contrast, negative emotions like "Angry," "Anxious," "Bored," and "Sad" exhibit a more dispersed distribution with less pronounced peaks, suggesting a less stable and consistent rhythmic frequency. The density plots highlight that users experiencing positive emotions not only tend to have higher levels of coherence, they also have more stable frequencies, whereas those reporting negative emotions display a broader range of frequencies. Overall, this distribution indicates that positive emotions are associated with more stable and harmonious physiological rhythms.

To further investigate the stability (variability) in HRV frequencies across different coherence levels and emotional states, we analyzed the standard deviation of coherence/resonance frequencies within sessions and between the same users' sessions. Figure 8(a) and (b) shows the frequency variability by coherence level and by emotion, respectively. Figure 8(a) shows the results of the analysis of frequency variability revealing significant insights into the relationship between coherence levels and frequency stability. Sessions were segmented into 128-second intervals with a 75% overlap, each with a coherence frequency, and summary statistics were calculated across all segments from all sessions. The mean and standard deviation in the frequency for each coherence level shows a clear trend: as the coherence level increases, both the mean and standard deviation in the frequency decrease. Specifically, the mean standard deviation in coherence frequency ranges from 0.0533 Hz in the 0–1 level to 0.0023 Hz in the 5 + level. Levene's test[55] for homogeneity of variances yields a test statistic of 110122.1668 with a p-value of < 0.0001, indicating a significant difference in the standard deviations across coherence levels. This finding is further supported by the post-hoc Tukey HSD test, which shows significant differences in mean standard deviations of frequencies between all pairs of coherence levels (p-adj < 0.0001) for all comparisons. The largest mean difference is observed between the 0–1 and 5 + levels (-0.051), while the smallest difference is between the 4–5 and 5 + levels (-0.0018). These results suggest that higher coherence levels are associated with more stable frequencies in the HRV spectrum, as evidenced by lower means and standard deviations. The significant differences between all coherence levels highlight the robustness of this relationship, indicating that as users achieve higher coherence, their heart rhythm pattern becomes more stable and consistent. This stability within sessions suggests that once participants settle into their natural, individual coherence/resonant frequency, they are stable at this frequency.

Figure 8(b) shows how the stability of the frequency varies significantly across different emotion categories. Users who reported positive emotions such as "Peaceful," "Happy," "Excited," and "Content" exhibited lower average standard deviations in their frequencies (0.0117 to 0.0130 Hz), indicating higher stability. In contrast, users who reported negative emotions like "Angry," "Anxious," "Bored," and "Sad" had higher average standard deviations (0.0164 to 0.0182 Hz), reflecting less stability. Levene's test and subsequent post-hoc Tukey HSD test confirm that these differences are statistically significant, with p-values of < 0.0001. This suggests that individuals' emotional states play a significant role in modulating the stability of the heart's rhythmic pattern, with positive emotions being associated with more coherent and regulated physiological states.

The analysis of user data across sessions for the two years reveals that the majority of users exhibit high stability in their frequency from session to session. Taking the standard deviation across common coherence frequencies from each session, most users have an average standard deviation below 0.012 Hz. This indicates that users generally maintain a consistent heart rhythm frequency during their biofeedback sessions, suggesting that their unique natural coherence/resonant frequency remains the same across sessions.

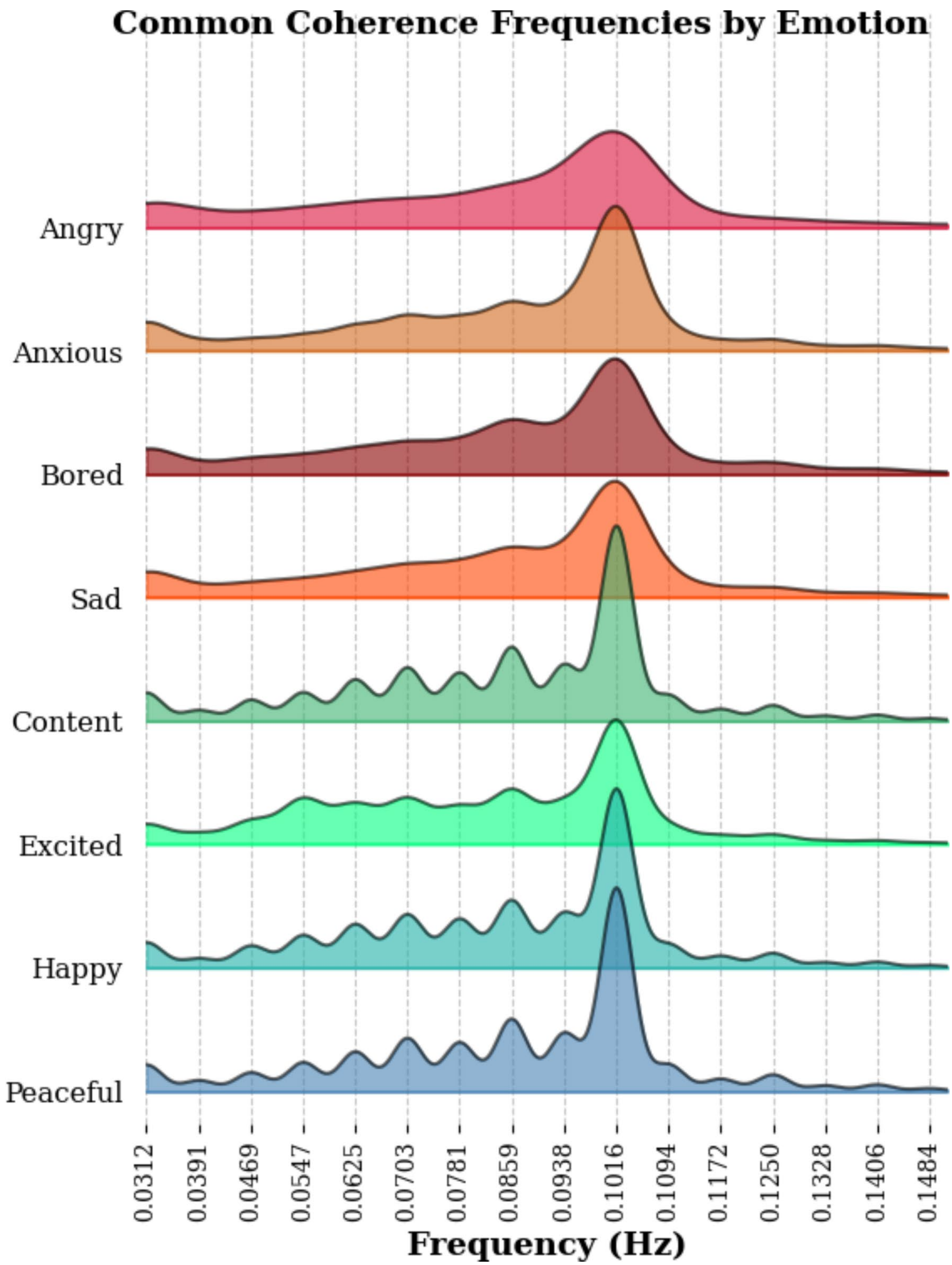

Fig. 7. Distribution of common coherence frequencies by emotion.

Discussion

The results of our global study provide important insights into the relationship between the stability of the coherence/resonance frequencies and emotional states, as measured through Heart Rate Variability data in Inner Balance app users in a real world setting. Our analysis, utilizing the largest dataset ever studied in the HRV biofeedback field, comprising data from over 1.8 million sessions, uncovered several new key findings that enhance our understanding of heart rhythm coherence biofeedback and its implications for interventions to enhance emotional and physiological well-being. First, the regularity in users naturally achieving a stable

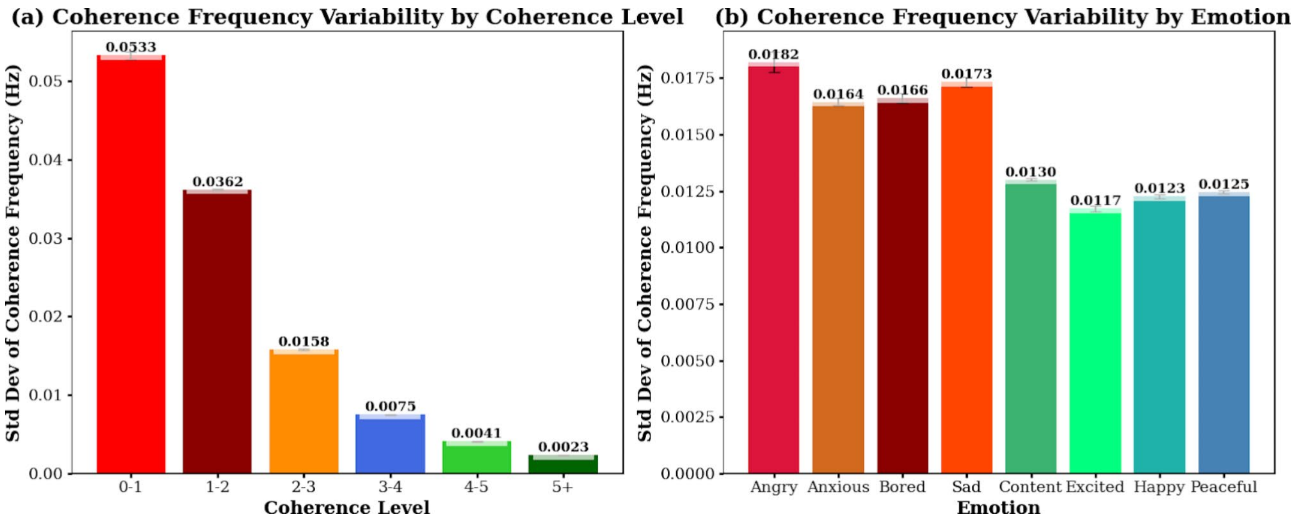

Fig. 8. (**a**) Coherence frequency variability by coherence level (**b**) coherence frequency variability by emotion.

coherence frequency within and across sessions suggests that practice of the HeartMath emotional regulation techniques combined with HRV coherence feedback are effective in inducing and sustaining a stable state of physiological coherence without the need to first determine one's resonant frequency. The spectral analysis of Inter-Beat Interval (IBI) data established that the most common frequency is around 0.10 Hz during practice sessions across all coherence scores with the exception of the 0–1 level. This was not surprising as numerous studies have found this frequency is associated with the baroreflex system which regulates short-term blood changes[56] and is at the center of the Coherence Range where frequency entrainment of the respiratory, beat-to-beat blood pressure and heart rhythms and increased heart-brain synchronization typically occurs[4,26]. What was surprising is that for many of the more experienced users with the highest levels of heart rhythm coherence, their frequency was in the lower end of the Coherence Range (see Fig. 4). In addition, as shown in Fig. 5, these lower frequencies have the highest overall coherence scores. Our analyses produced very strong p-values, which show that our findings are reliable. The large dataset contributed to the strength of these results, reinforcing the validity of the statistical inferences drawn.

The heart's optimal function relies on a complex interplay between the central nervous system and the intrinsic cardiac nervous system (ICNS) located within the heart itself. Neurocardiology research has extensively investigated the anatomy and functions of the ICNS and its neural connections with the brain[57]. The intrinsic cardiac nervous system has both short-term and long-term memory functions, which can influence HRV and afferent activity related to BP, rhythm, rate, and hormonal factors[17]. The ICNS exhibits both short-term and long-term memory capabilities, which can modulate heart rate variability (HRV) and afferent activity associated with blood pressure, cardiac rhythm, heart rate, and hormonal factors. Comprising sensory, interconnecting, afferent, and motor neurons, the ICNS can function autonomously from central neuronal control. The extensive network of these intrinsic cardiac neurons is so sophisticated that it has been characterized as a "little brain" within the heart, highlighting its importance in cardiac regulation and adaptation[58].

The observation of higher coherence levels occurring at the lower frequencies may be related to the findings in neurocardiology research that was undertaken after the observation in a auto-transplant study of dog hearts where the levels of HRV were much higher than expected suggesting that a significant amount of HRV may be generated by the heart itself[59]. In long-term recordings from single afferent neurons in beating hearts and simultaneously from extrinsic cardiac neurons, it was discovered that the lower frequency rhythms were generated from feedback loops between the sensory neurons in the heart and the intrinsic cardiac nervous system[60]. These rhythms appeared to be associated with deeper states of relaxation and cardiovascular system efficiency as the stability and frequency of these low frequency rhythms were disrupted by stimulation of efferent sympathetic inputs to the intrinsic cardiac nervous system[17].

As mentioned earlier, the coherence model emphasizes the importance of the neural patterns and their stability in the afferent cardiovascular inputs to the brain on emotional stability and cognitive functions. This aspect of the model was informed by the seminal research and "baroreceptor hypothesis" first introduced by psychophysiologists John and Beatrice Lacey who identified a causal relationship between the heart's afferent inputs and cognitive performance[61,62]. This work was significantly advanced by Wölk and Velden, who identified that it was not the amount or amplitude of the afferent inputs to the brain as the Lacey's had thought, rather it is the rhythm pattern and its stability that most important in influencing neurological functioning[63,64]. Studies in neurocardiology have since established that the interactions between the heart and brain are much more complex than previously thought and that patterns of afferent activity occur over time scales ranging in milliseconds to minutes[63,65]. Heart-brain synchronization over shorter time periods (seconds) was a key aspect of Wölk and Velden findings, while synchronization across much longer time periods (minutes) is an important aspect of The Heart Rhythm Coherence Hypothesis[4].

Our study also revealed significant differences in coherence scores based on self-reported emotional states recorded at the end of each session. Positive emotions, such as "Excited," "Happy," and "Peaceful," were associated with higher coherence scores, reflecting more stable physiological states. Conversely, negative emotions like "Angry" and "Anxious" were linked to lower coherence scores and more dispersed frequency distributions, indicative of less stable physiological states. These findings suggest that the self-activation of a positive emotion in step 2 of the techniques facilitates achieving and stabilizing a coherence state which can positively influence well-being, emotional stability and reduce mental and emotional stress.

Analysis of HRV metrics, such as SDNN, Mean IBI, LF Power, HF Power, RMSSD, and LF/HF Ratio, demonstrated significant changes across different coherence levels. The observed trends suggest a complex interplay between respiration, beat-to-beat blood pressure regulation and activity in both the afferent and efferent activity in the autonomic nervous system. For instance, the expected increase in the LF/HF ratio in higher coherence levels was due to large an increase in low-frequency power, which is often associated with enhanced baroreflex function and increased afferent vagal traffic[18,26,66]. This increase in low-frequency power is typically due to an increase in the amplitude of the HRV rhythm and by a more regular sine-wave like rhythmic heart rate pattern in the LF region of the spectrum[4,26,67]. However, the increased order in the heart rhythm results in a lower SDNN and RMSSD, despite either no change or an overall increase in the amount (amplitude) of the HRV. This is because SDNN and RMSSD are more sensitive to capturing larger changes in the beat-to-beat interval variations, which are reduced in the more ordered distribution of the inter-beat-intervals when the rhythm is more coherent[68].

Therefore, it is important to consider the context in which these measures are being interpreted and understand that traditional interpretations of the SDNN and RMSSD do not capture the nuances of coherence or resonance states. In typical HRV analysis, SDNN and RMSSD values are often interpreted as indicators of how much HRV occurred in a given analysis period with higher values being associated with greater amounts of overall HRV (SDNN) or increased parasympathetic activity (RMSSD)[18]. However, during high coherence states, where the heart rate variability pattern becomes more regular and rhythmic, the increased regularity reduces the time between successive heartbeats, leading to lower RMSSD values even when the overall HRV may actually be increased as indicated by an increased LF power. In a sine wave pattern, the differences between adjacent points are smallest near the peaks and troughs, and largest at the midpoints between peaks and troughs. However, these differences change gradually and predictably. An example of this can be visually seen in Fig. 1 where the IBIs are indicated by dots. In the highly coherent rhythm (1c), the time between consecutive pairs of heartbeats is clearly less than in the other less coherent rhythms. As the RMSSD looks at the differences in the time intervals between consecutive heartbeats, the RMSSD is reduced in this context, although the amplitude of the rhythm is not. Similarly, the overall variability measured by SDNN is reduced due to the more predictable and consistent heart rate pattern, with smaller beat-to-beat differences. In this context, the lower RMSSD and SDNN does not imply reduced HRV or vagal activity but rather that different measures such as frequency domain measures are required to characterize these more ordered coherent states. This is equally true in both resonant frequency breathing and HRV coherence contexts. In this context the coherence measure, LF power and the LF/HF ratio provide a more appropriate measure as long as it is understood that the increased LF/HF ratio does not indicate increased sympathetic activity in this context. It is actually the opposite and indicates increased vagal (parasympathetic) activity in this context[18,26,66]. Therefore, while SDNN and RMSSD are valuable metrics, their interpretation must be contextualized highlighting the need for a more nuanced understanding in coherence research.

The body of empirical evidence supporting the benefits of coherence-based interventions highlights the practical applications of HRV coherence biofeedback to enhance self-regulatory capacity in both clinical settings and daily life across a broad range of applications such as law enforcement and military, classrooms, corporate, and personal development contexts. By teaching techniques that increase coherence, combined with HRV feedback practice, these interventions have been shown to improve emotional regulation, cognitive function, and overall well-being. The widespread availability of mobile applications like the Inner Balance Trainer and emWave Pro for clinical and educational applications facilitates the integration of such practices into everyday routines, making coherence based self-regulation practices accessible to a global audience.

However, there are limitations to our study that need to be highlighted. This study is performed in real-world settings, which demonstrates its relevance in a broad global population, but it does not have the same control as an experiment by design. Support is provided by reproducing results such as the 0.10 Hz coherence frequency and association with positive emotions, which is consistent with past controlled studies[4,25,26]. It will be good to perform future controlled studies that test the new findings here.

One significant limitation is the lack of pre-session emotion report data, which means we do not have a reference baseline to compare to for any changes in emotional state or intensity of emotion due to the coherence practice of users. This limitation makes it challenging to fully understand the impact of coherence practices on emotional states without knowing the initial emotional state of the participants. We also did not have any baseline HRV data from the users before starting the practice session so we were not able to assess changes in users HRV, although this has been done in other studies[4,25,32,37,47].

Future research could expand on these findings by exploring the long-term effects of coherence feedback practice and investigating the specific mechanisms through which coherence practices influence ANS activity and cognitive functions. Additionally, studying the applications of coherence-based techniques in various clinical populations could provide deeper insights into their therapeutic potential. Our study demonstrates that coherence-based interventions are not only beneficial for individual health but could also contribute to broader public health efforts aimed at stress reduction and emotional well-being. With the increasing interest in HRV biofeedback and coherence practices, continued research in this field holds promise for advancing our understanding of the intricate connections between physiology, emotion, and health.

Conclusion

This global study analyzed data from the largest dataset ever studied in the HRV biofeedback field, comprising 1.8 million user sessions collected from Inner Balance app users during 2019 and 2020. We focused on HRV Coherence, which is linked to improved emotional stability and cognitive function. The most common frequency associated with Coherence was identified at 0.10 Hz. This is near the center of the Coherence Range where frequency entrainment of the respiratory, beat-to-beat blood pressure and heart rhythms and increased heart-brain synchronization typically occurs. However, a surprising finding was that many users with the highest levels of Coherence fell within a lower range from 0.04 to 0.10 Hz.

Most users exhibited high stability (standard deviation < 0.012 Hz) in their coherence frequencies from session to session, and their stability within a given session increases with increasing Coherence. The insights gained from this extensive dataset suggest that by instructing users to breathe deeper and slower and find a rhythm that's comfortable, they naturally find their unique resonant frequency. This supports the importance of techniques that instruct users to breathe deeper and slower than usual but find a rhythm that is comfortable, allowing users to find their own individual HRV coherence or resonant frequency and sustain it.

The observed trends in HRV metrics, such as SDNN, Mean IBI, LF Power, HF Power, RMSSD, and LF/HF Ratio, suggest a complex interplay between coherent states and autonomic nervous system activity. Higher coherence levels are associated with more stable and regulated physiological states, as evidenced by significant changes in these HRV metrics. It was also shown how and why it is important to consider the context in which these measures are being interpreted and understood and that traditional interpretations of the SDNN and RMSSD do not capture the nuances of coherence or resonance states.

This study also helps clarify the relationship between common HRV coherence frequencies and emotional states by revealing that positive emotions are associated with higher coherence scores and more stable coherence frequencies. In contrast, negative emotions exhibit more dispersed frequency distributions, indicating less stable physiological states. The insights gained from this extensive dataset provide a strong foundation for future research and the development of targeted interventions aimed at enhancing emotional and physiological well-being through HRV biofeedback and coherence practices.

Materials and methods

Anonymized HRV data from a global population of emWave Pro software and Inner Balance app users who elected to upload their session data to the HeartCloud server was used in this study. The dataset for the years 2019 and 2020, comprised 70,041 unique users with a total of 4,637,295 HRV coherence practice sessions. Of these users, 43% were female, 55% were male, and 2% did not specify their gender. The average age of participants was 49 years, with a standard deviation of 10.7 years. Out of the total sessions, 1,884,216 were analyzed, focusing on those who also reported emotions and had durations of 3 to 15 min. The app interfaced with either a wired or Bluetooth-connected pulse photoplethysmogram (PPG) sensor, which sampled at 125 Hz. We utilized established techniques for HRV analysis, including removal of artifacts, Welch's method for Power Spectral Density (PSD) calculation, linear interpolation for data resampling, and detrending procedures. The dataset included: UserUuid (a blinded unique identifier for each user), IBIStartTime (the start time of the Inter-Beat Interval measurement in Unix timestamp), IBIEndTime (the end time of the Inter-Beat Interval measurement in Unix timestamp), LiveIBI (a string of comma-separated values representing time intervals between heartbeats), AvgCoherence (the average coherence across the session), Country/Region (the user's geographic location), and Emotion (self-reported user emotion following the session).

To begin, standardization of the Emotion column was carried out to consolidate non-English terms and merge similar categories. For example, all instances of 'keine Stimmung' and 'Keine Stimmung' were replaced with 'No Emotion', while terms such as 'ängstlich', 'Ängstlich', and 'Gelangweilt' were standardized to 'Anxious'. Any records containing 'No Emotion' or with AvgCoherence ≤ 0 were removed to maintain the data quality. Next, the number of sessions per unique user was calculated and a new column reflecting these counts was created. To ensure session quality, only sessions lasting between 3 to 15 minutes were included; this range was chosen to better reflect users focused on a biofeedback session to ensure data integrity. The UNIX timestamps (IBIStartTime and IBIEndTime) were converted to readable date-time formats. Subsequently, IBI data points that did not fall within the range of 400 to 2000 ms were excluded. The LiveIBI data underwent validation to retain only non-empty entries. To facilitate analysis, the dataset records were further classified into predefined session AvgCoherence categories: '0–1' (AvgCoherence greater than 0 and between 1 exclusive), '1–2' (AvgCoherence between 1 inclusive and 2 exclusive), '2–3' (AvgCoherence between 2 inclusive and 3 exclusive), '3–4' (AvgCoherence between 3 inclusive and 4 exclusive), '4–5' (AvgCoherence between 4 inclusive and 5 exclusive), and '5+' (AvgCoherence ≥ 5).

For coherence/resonant frequency analysis, the initial 30 seconds of IBI data from each session were skipped to allow for the time it takes users to settle into a session to improve data consistency. The IBI data, initially recorded in milliseconds, was converted to seconds for improved numerical stability. This data was then linearly interpolated to create a regularly spaced time series at 2 Hz, facilitating accurate spectral analysis. The time series was segmented into windows of 128 s with a 75% overlap to maximize data utilization and reduce spectral leakage. To remove linear trends that could introduce artificial low-frequency components, a detrending procedure was applied to the resampled IBI time series. Each segment was tapered using a Hanning window function to further reduce spectral leakage at segment boundaries. Power Spectral Density (PSD) was calculated using Welch's method.

Within each 128-second window, the frequency corresponding to the peak PSD value was identified as the coherence frequency confined within the physiological range of 0.03 to 0.4 Hz. This method provided robust estimates of the power distribution across different frequency components of the time series. Various statistical measures for coherence frequencies—such as mean, standard deviation, mode, median, maximum, and minimum—were computed for each session. Non-informative sessions, which lacked a mode or were bimodal, were removed from the analysis. Additionally, to derive further insights, the standard deviation of the most common coherent frequency was calculated for each user across sessions and this was averaged across users, providing a comprehensive view of user coherence stability across sessions. Additionally, the mean and maximum amplitudes of coherence frequency spectra were calculated. Finally, visualizations were generated to illustrate coherence frequencies by coherence level and various HRV metrics, such as MeanIBI, SDNN, LF Power, HF Power, RMSSD, and LF/HF Ratio. Figures were also created to show common coherence frequencies by emotion, and the standard deviation in coherence frequencies by coherence level and emotion.

Given the large sample size in our study, the assumption of normality for the distribution of sample means is supported by the Central Limit Theorem. This justifies the use of parametric tests such as t-tests and ANOVA. Additionally, all data were assumed to be independent and identically distributed, which is a prerequisite for these statistical analyses. Our analyses were performed over very large datasets that produced strong p-values, which would hold true even if we reduced our degrees of freedom to accommodate these assumptions.

Ethics statement

This study was conducted as a secondary analysis of existing data, utilizing anonymized HRV biofeedback session data from a global population of users. The analysis was performed in compliance with the privacy policy and data use agreement accepted by users of the HRV biofeedback application and was approved by the Kaunas University Regional Ethics Committee for Biomedical Investigations (No.AMI_GML_21). Informed consent was obtained from all subjects and/or their legal guardian by their acceptance of the terms of service and privacy policy of the HRV biofeedback application which grants use of anonymized data for research. This agreement clearly informs the user that anonymized data may be used for research purposes and constitutes written informed consent. All personal identifiers were removed from the dataset prior to analysis, ensuring that individual users cannot be identified from the research findings and strict confidentiality measures were maintained throughout the study to protect the privacy of the users whose data was analyzed. The aim of this research is to contribute to the scientific understanding of HRV biofeedback and its potential benefits, with the ultimate goal of improving health and well-being for the broader population and the global nature of the dataset ensures that the findings are representative of a diverse population, promoting equitable distribution of the potential benefits of this research. This research was conducted in accordance with the Declaration of Helsinki and adheres to the ethical guidelines for human protection.

Data availability

All datasets analyzed in the current study are available from the corresponding author on reasonable request.

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Author contributions

S.B., design of study, data and statistical analysis, writing; N.P., design of study and analyses, writing; M.A., organization of data collection, integration, and cleaning; M.M., MR, AV, design of study and analyses, data visualization, writing; R.M., writing Introduction and discussion, coordinating data collection.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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