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Article

Understanding the biomechanics of music-induced emotions: A study of physical responses to rhythm and melody

Wenjing Wang

School of Music, Nanjing Xiaozhuang University, Nanjing 211171, China; 13809035383@126.com

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Abstract: This study investigated the biomechanical aspects of music-induced emotions through a comprehensive analysis of physical responses to rhythm and melody among 28 participants in China. Using high-precision physiological monitoring equipment, this study measured Heart Rate Variability (HRV), Muscle Activation (MA), Galvanic Skin Response (GSR), and Body Sway Patterns (BSP) in response to standardized musical stimuli. Results revealed distinct physiological response patterns between rhythmic and melodic elements. Rhythmic stimuli elicited more robust cardiovascular responses, with mean HRV increases of 15.4 ± 1.7 bpm during fast rhythms (132–144 BPM) compared to 5.2 ± 1.1 bpm for melodic features ($p < 0.001$, $d = 1.24$). Muscle tension significantly correlated with rhythmic elements ($r = 0.81$, $p < 0.001$) and demonstrated progressive adaptation, with response latencies decreasing from 285 ± 42 to 156 ± 28 ms over exposure time. Melodic features induced more varied responses, with ascending phrases increasing HRV by 4.8 ± 0.9 bpm while sustained notes decreased it by 3.6 ± 0.8 bpm. Analysis of self-reported emotions strongly correlated with physiological measures, particularly for high-intensity emotional states (concordance rate: 92.1 ± 3.2%, $\alpha = 0.91$). The study revealed a hierarchical organization in rhythm processing, with MA showing the quickest response (178 ± 25 ms), followed by HRV (245 ± 35 ms) and GSR (475 ± 62 ms). These findings provide quantitative evidence for the differential impact of rhythmic and melodic elements on physiological responses, contributing to this work's understanding of music-induced emotional processing and its potential applications in therapeutic contexts.

Keywords: music-induced emotions; biomechanics; physiological responses; rhythm; melody; heart rate variability; muscle tension

1. Introduction

Music's capacity to evoke Emotional Responses (ER) represents one of the most profound and universal human experiences, transcending cultural and linguistic boundaries [1]. Recent advances in biomechanical measurement techniques have enabled increasingly precise investigations of the physiological manifestations of these ERs [2–4]. While extensive research has examined the psychological aspects of Music-Induced Emotions (MIE), the specific biomechanical pathways through which musical elements trigger physical responses remain incompletely understood [5,6]. Previous studies have established that musical experiences engage multiple physiological systems simultaneously [7–9]. Research has demonstrated correlations between rhythmic patterns and cardiovascular responses, while other investigations have identified specific relationships between melodic structures and Muscle Tension (MT) [10,11]. However, these studies typically focused on isolated physiological parameters rather than examining the integrated biomechanical response to musical stimuli [12,13]. This fragmented approach has limited our understanding of how musical elements—particularly rhythm and melody—interact to produce coordinated physiological responses.

The relationship between music and physiological response involves complex interactions between auditory processing, emotional interpretation, and physical manifestation [14–16]. Recent neuroimaging studies have revealed that music processing activates the brain's emotional and motor centers, suggesting direct neural pathways between musical perception and physical response [17–19]. However, the temporal dynamics and relative contributions of rhythmic versus melodic elements to these responses remain unclear, particularly regarding their biomechanical manifestations [20,21]. The present study addresses these knowledge gaps by investigating the biomechanical aspects of MIE through a comprehensive examination of physical responses to rhythm and melody [22].

Specifically, this research aims to:

(a) Quantify and compare the physiological responses to rhythmic and melodic elements in music, focusing on Heart Rate Variability (HRV), Muscle Activation (MA), and Galvanic Skin Response (GSR);
(b) Examine the temporal dynamics of these responses, including onset latency, adaptation patterns, and recovery characteristics;
(c) Investigate the correlation between objective physiological measurements and subjective emotional experiences;
(d) Analyze the interaction effects between rhythmic and melodic elements in generating integrated physical responses.

This investigation employs high-precision physiological monitoring equipment and standardized musical stimuli to capture detailed biomechanical responses [23,24]. By examining isolated and combined effects of rhythm and melody, this study provides insights into how musical elements trigger and modulate physical responses [25,26]. Understanding these mechanisms has significant implications for music therapy, performance psychology, and emotional regulation techniques [27]. The findings contribute to theoretical understanding and practical applications in multiple domains. Theoretically, this research advances our knowledge of the physiological pathways through which music influences emotional states [28]. The results inform the development of music-based interventions for emotional regulation and therapeutic applications while providing insights relevant to performance optimization in musical contexts [29,30].

This paper is structured as follows: First, we present a comprehensive review of theoretical frameworks regarding MIE and their physical manifestations in Section 2. We then detail our experimental methodology, including participant selection, measurement protocols, and analytical approaches in Section 3. Section 4 separately presents findings on physical responses to rhythm and melody, followed by comparative analyses [31–34]. We discuss the implications of these findings for theoretical understanding and practical applications in various fields in Section 5. Finally, Section 6 provides the conclusion of the work.

2. Theoretical background

2.1. Overview of music and emotion

Music has long been recognized as a profound influencer of human emotion, engaging listeners across cultures and personal experiences. The relationship between music and emotion is complex and multifaceted, involving psychological, neurological, and physiological processes. Existing theories on how music elicits ER often fall within three primary domains: cognitive appraisal theories, embodied theories, and neurobiological perspectives. Cognitive appraisal theories suggest listeners interpret and assess musical elements based on prior experiences, memories, and cultural contexts, which evoke ER. According to this perspective, emotions emerge as a cognitive reaction to music's symbolic and structural elements, such as harmony, tempo, and rhythm. For instance, a minor key might be associated with sadness or melancholy based on culturally embedded conventions, while a significant key often signifies joy. This appraisal mechanism compares musical cues and an individual's emotional memory, linking past experiences to present emotional states induced by music.

Embodied theories propose that ER to music is generated through the direct physical and sensory experiences that music induces. These theories emphasize how rhythm, tempo, and dynamics can synchronize with bodily responses, such as HRV, breathing, and movement. For example, a fast rhythm can naturally align with increased HRV or arousal, while a slow, flowing melody may invoke a calming effect. Embodied theories highlight that MIE are not solely cognitive but are also physical, stemming from the body's visceral response to the music's dynamic qualities. This perspective aligns closely with the concept of music's contagion effect, where physical synchronization leads to an emotional experience—listeners physically feel the music's energy, and this "felt emotion" can lead to emotional states.

Neurobiological perspectives provide insights into the brain's role in processing MIE, mainly through the limbic system and dopamine pathways. Studies show that music activates brain regions associated with reward, pleasure, and emotional regulation, including the amygdala, hippocampus, and ventral striatum. When listening to music, the brain releases dopamine, a neurotransmitter linked to pleasure and motivation, which is notably active in peak emotional moments within a musical piece. Neuroimaging studies reveal that music uniquely activates these emotional pathways without any explicit or verbal stimuli, making it a powerful trigger for emotions through purely auditory means.

These theories suggest music influences emotion through cognitive, physical, and neurochemical processes. Music's ability to evoke emotion arises from a dynamic interplay where listeners cognitively interpret musical elements, embody physical responses to rhythmic and melodic structures, and experience a neurochemical response that reinforces the emotional impact. This theoretical foundation underscores music's capacity to act as a universal yet deeply personal emotional language, with its influence on human emotion being both highly subjective and biologically ingrained. Understanding these foundational theories is crucial for studying the biomechanics of MIE, as it provides a framework for interpreting the physical manifestations of ER to rhythm and melody in listeners.

2.2. Biomechanical aspects of emotion

ER to music and other stimuli are often accompanied by distinct physiological changes, providing a measurable link between psychological experiences and physical reactions. Biomechanical indicators, such as MA, HRV, and skin conductance, are crucial markers in identifying and analyzing these responses. Each indicator reflects a different aspect of the body's reaction to emotional stimuli, offering insights into how emotions manifest physically.

1) MA is one of the most direct physical responses to emotion. When experiencing strong emotions—whether excitement, fear, or sadness—MT often changes in response. For example, joyful or energizing music might prompt involuntary movements or dance, activating large muscle groups, while a tense or distressing piece might cause subtle tension in the facial muscles or upper body. Electromyography (EMG) can track these changes in MA, capturing the intensity and pattern of responses across various muscle groups. In studies of music-induced emotion, EMG measurements provide valuable data on how rhythm and melody influence bodily movement, revealing patterns of activation that align with specific emotional experiences.
2) HRV, the fluctuation in time intervals between consecutive heartbeats, is a sensitive indicator of emotional arousal and autonomic nervous system activity. Emotional states like relaxation or contentment correlate with high HRV, indicating greater adaptability and balance in autonomic response. Conversely, stress, anxiety, or intense excitement often show reduced HRV, signaling heightened sympathetic nervous activity. Changes in heart rate and HRV during music listening are often in sync with emotional shifts, with faster rhythms and energetic melodies potentially increasing and decreasing HRV, while slower, soothing music might have a calming effect. HRV is thus a reliable biomechanical measure for tracking emotional shifts influenced by musical elements.
3) Kin conductance, or GSR, measures the skin's electrical conductivity, which varies with sweat gland activity and is influenced by arousal levels. Emotional arousal—positive or negative—tends to increase skin conductance due to sympathetic nervous activation, stimulating perspiration even at minimal levels. Music that evokes strong emotions, such as excitement, fear, or surprise, typically causes a detectable rise in skin conductance, reflecting the body's immediate autonomic response to emotional stimuli. Skin conductance measurements are instrumental in music-emotion studies because they provide a real-time, non-invasive assessment of arousal, allowing researchers to correlate peaks in GSR with specific musical passages.

Each biomechanical indicator— MA, HRV, and skin conductance—provides a distinct lens for analyzing physical responses to emotional experiences. When combined, these measures offer a comprehensive view of the body's physiological reaction to music, helping to quantify the connection between auditory stimuli and emotional impact. By tracking these biomechanical responses, researchers can objectively study the effects of rhythm and melody, paving the way for deeper insights into how music triggers subtle and overt physical manifestations of emotion.

2.3. Role of rhythm and melody in emotional triggers

Rhythm and melody are two core components of music that uniquely contribute to the emotional experiences it evokes. While rhythm primarily influences physical responses and movement, melody plays a significant role in shaping the emotional nuances of a listener's experience. Together, they create a dynamic interplay that engages the body and mind, forming a holistic emotional response to music.

1) Rhythm is closely associated with bodily movement and is often the driver behind physical responses to music. Its repetitive structure and tempo resonate with the human body's natural rhythms, such as heartbeat, breathing, and walking cadence. This alignment allows rhythm to easily synchronize with bodily functions, evoking an instinctual response often characterized by tapping, swaying, or dancing. Fast, upbeat rhythms can heighten energy and arousal, prompting increased HRV and MA, while slower rhythms tend to calm the body, inducing relaxation. Rhythm's capacity to engage the body in movement also facilitates entrainment, a process where an external beat aligns with an individual's internal biological rhythms. This synchronization between external and internal rhythms reinforces rhythmic music's power to evoke physical engagement, laying the foundation for an emotional experience that begins with movement.
2) Melody, in contrast, is more complex and nuanced, often engaging cognitive and emotional processes directly. A melody's pitches, harmony, and progression sequence elicit various emotions by tapping into cultural and personal associations with specific tonalities and intervals. For instance, significant melodies are often perceived as uplifting or happy, while minor melodies can evoke sadness or introspection. Melody can carry a narrative quality, leading listeners through a succession of emotional states by creating tension, resolution, and variation in pitch. This evokes subtle emotional reactions, such as nostalgia, tranquility, or suspense, tied less to physical movement and more to reflective or affective states. The emotional impact of melody is compelling in its ability to elicit imagery, memories, or emotional memories, allowing listeners to connect deeply on a personal level.

When combined, rhythm and melody create a rich tapestry of emotional triggers. Rhythm grounds the listener in a physical, visceral experience, while melody engages cognitive and ER, weaving together a layered emotional response that is both embodied and interpretative. In fast-paced, rhythm-driven music with a cheerful melody, the listener may experience heightened physical and emotional excitement. Conversely, a slow rhythm paired with a melancholic melody can lead to introspection, with subdued physical responses and a reflective emotional state.

3. Methodology

3.1. Participant selection

The study comprised 28 participants recruited from various regions across China, with the sample size determined through G*Power 3.1 software analysis (α = 0.05, power = 0.80, Cohen's d = 0.6). As shown in **Table 1**, the participant pool represented a balanced demographic distribution, with 15 females (53.6%) and 13 males (46.4%) ranging in age from 18 to 35 years (M = 24.6, SD = 4.2). The educational composition of the sample population demonstrated diversity, encompassing undergraduate students (42.9%), graduate students (35.7%), and young professionals (21.4%). Geographic representation was strategically planned across four major regions of China, as detailed in **Figure 1**. The distribution included Eastern China (Shanghai and Jiangsu Province, n = 8), Northern China (Beijing and Hebei Province, n = 7), Southern China (Guangdong Province, n = 7), and Central China (Hunan Province, n = 6), ensuring broad regional representation.

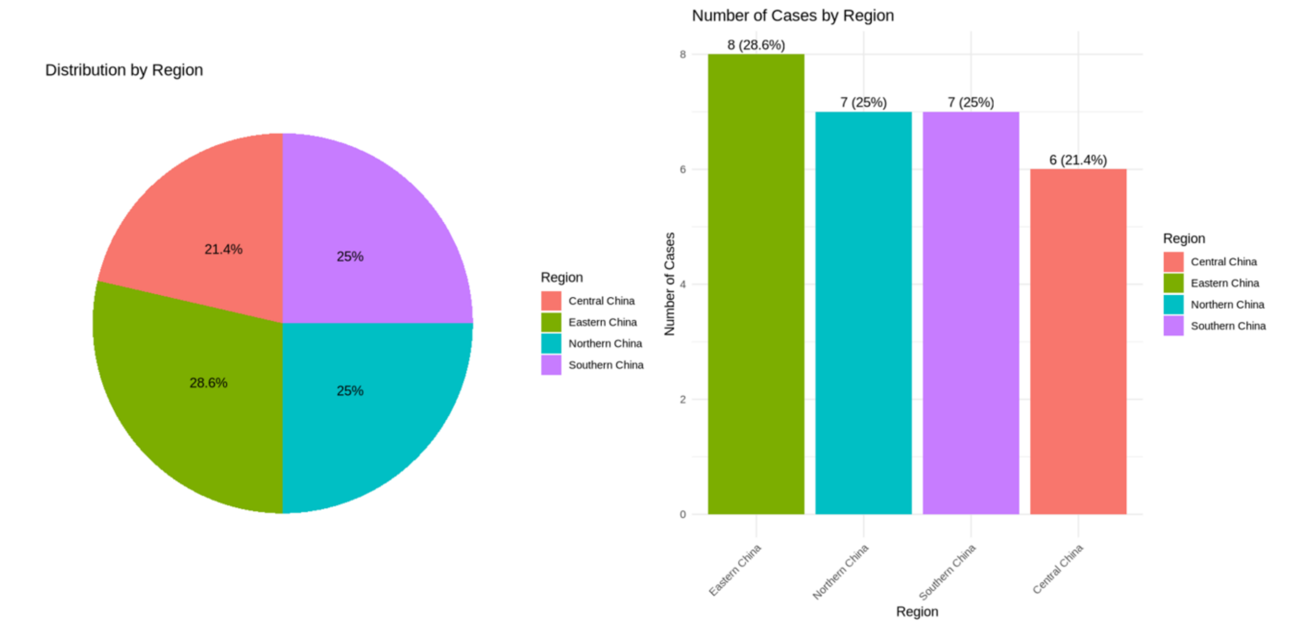

Figure 1. Geographic distribution of participants.

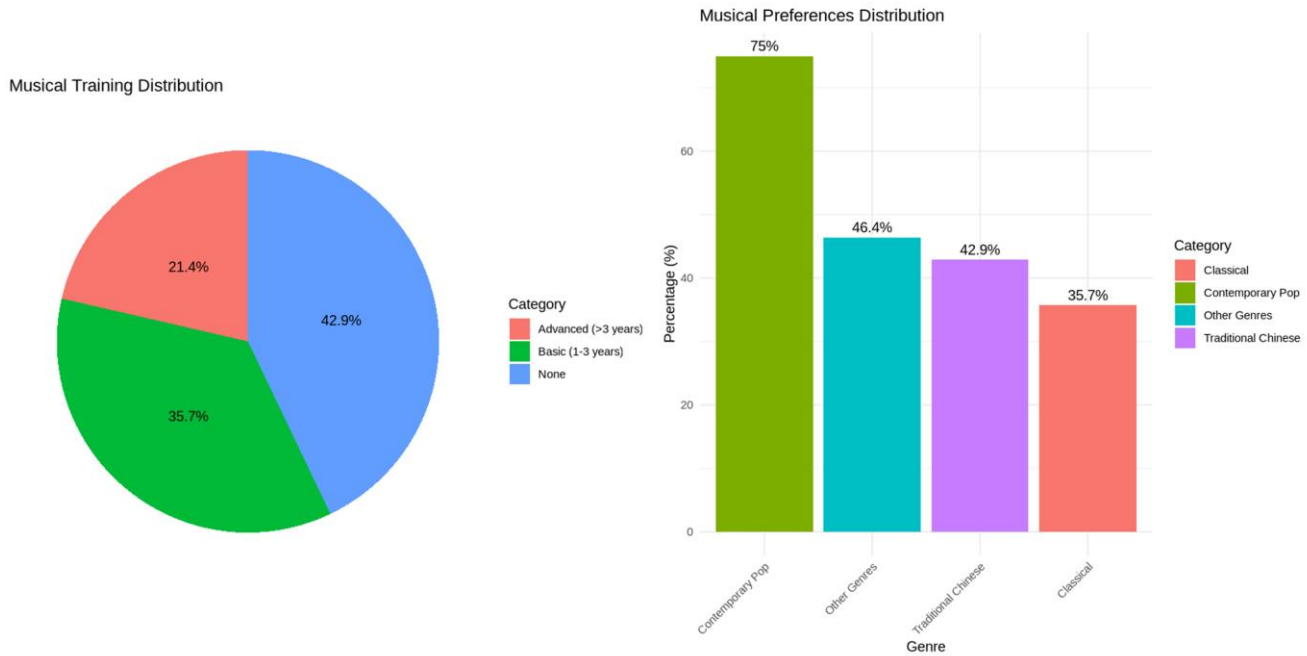

Figure 2. Musical background and preferences.

Figure 2 illustrates participants' varied musical backgrounds, with 42.9% reporting no formal musical training, 35.7% having basic training (1–3 years), and 21.4% possessing advanced training (> 3 years). The same table reveals diverse musical preferences, with a notable inclination toward contemporary pop (75.0%), followed by traditional Chinese music (42.9%), classical music (35.7%), and other genres (46.4%).

The recruitment process, documented in **Table 2**, began with 35 potential participants, achieving a final retention rate of 80% (n = 28). The comprehensive screening process, detailed in **Table 3**, involved multiple stages, including online questionnaires, phone interviews, health assessments, hearing tests, and psychological screening. This rigorous selection process ensured high-quality data collection while maintaining participant safety and study validity.

Table 1. Participant demographic distribution.

Characteristic	**Category**	**Number (*n*)**	**Percentage (%)**
Gender	Female	15	53.6
	Male	13	46.4
Total		28	100
Age Groups	18–23 years	12	42.9
	24–29 years	10	35.7
	30–35 years	6	21.4
Total		28	100
Educational Status	Undergraduate	12	42.9
	Graduate	10	35.7
	Young Professional	6	21.4
Total		28	100

Study participation was contingent upon meeting strict inclusion criteria, as summarized in **Table 4**. All participants were required to be between 18–35 years old, possess normal or corrected-to-normal vision, demonstrate normal hearing range (verified through basic audiometry), and be right-handed (Edinburgh Handedness Inventory score > 40). Health-related inclusion criteria stipulated no history of neurological disorders, hearing impairments, or cardiovascular conditions. Additionally, participants were required to be fluent in Mandarin Chinese and have no professional music performance experience.

Table 2. Recruitment and retention statistics.

Stage	**Number (*n*)**	**Percentage (%)**
Initial Applications	35	100.0
Screened Out	5	14.3
Voluntary Withdrawal	2	5.7
Final Participants	28	80.0

Table 3. Participant screening results.

Screening Criterion	Passed (*n*)	Failed (*n*)	Withdrawal (*n*)
Online Questionnaire	32	3	0
Phone Interview	30	2	0
Health Assessment	29	1	0
Hearing Test	28	1	0
Psychological Screening	28	0	2
Final Participants	28	**7**	2

The recruitment strategy utilized multiple channels, including university bulletin boards, social media platforms (WeChat and Weibo), local community centers, and academic department mailing lists. The study offered monetary compensation (¥200 per session), transportation allowance, and flexible scheduling options to encourage participation and retention. Communication was maintained through dedicated WeChat groups. All recruitment and selection procedures received approval from the University Ethics Committee (Approval No. 2024-BM-028), the Local Health Authority Review Board, and the National Research Ethics Committee. Participants provided written informed consent after being thoroughly informed about the study objectives, procedures, data collection methods, right to withdraw, confidentiality measures, and potential risks and benefits. The screening outcomes (**Table 5**) demonstrate the effectiveness of our selection process, with all final participants meeting 100% of the inclusion criteria (**Table 6**).

3.2. Experimental design

The study employed a within-subjects repeated measures design conducted over eight weeks (February–April 2024) at the Sound Research Laboratory, focusing on physiological responses to varied musical stimuli. Each participant completed three sessions: initial screening and baseline assessment (Week 1), primary experimental session (Weeks 2–6), and follow-up validation (Week 8). All experimental procedures were conducted in a sound-isolated laboratory environment with controlled conditions (ambient temperature: 22 ℃–24 ℃, humidity: 45%–55%, background noise level: < 30 dB).

The experimental setup utilized high-precision physiological monitoring equipment alongside professional-grade audio presentation systems. Physiological data was collected using a Polar H10 chest strap monitor for HRV, Shimmer3 GSR+ unit for skin conductance, Delsys Trigno surface EMG electrodes for MT, and a chest belt pneumograph for respiratory rate, all sampling at 1000 Hz. Audio stimuli were presented through calibrated Sennheiser HD 660S headphones connected to a Focusrite Scarlett 2i2 interface, maintaining consistent output levels at 75 dB SPL.

Table 4. Musical stimulus characteristics and control parameters.

Category	Number of Pieces	Duration	Key Features	Normalization
Traditional Chinese	5	3 min	Pentatonic scale	−16 LUFS
Western Classical	5	3 min	Orchestral	−16 LUFS
Contemporary Pop	5	3 min	Modern arrangements	−16 LUFS
Control (White Noise)	1	3 min	Calibrated amplitude	−16 LUFS

The experimental protocol implemented strict control measures to ensure data quality and participant consistency. Participants were required to abstain from caffeine and alcohol for 24 h before testing, with sessions scheduled consistently between 9:00–11:00 AM to control for circadian variations. Each experimental session followed a standardized structure to maintain procedural reliability and data quality, as detailed in **Table 5**.

Table 5. Experimental session structure.

Phase	Duration	Key Activities	Data Collection
Setup	20 min	Sensor placement, System Calibration	Equipment checks
Baseline	10 min	Resting State Recording	All physiological measures
Stimulus	60 min	Randomized Music Presentation	Continuous recording
Recovery	10 min	Post-stimulus Baseline	All physiological measures
Debrief	20 min	Survey Completion	Subjective responses

Data quality assurance was maintained through continuous signal quality monitoring (minimum signal-to-noise ratio > 40 dB) and systematic artifact detection. Real-time monitoring protocols were established to ensure data integrity, with clear criteria for artifact rejection, including movement artifacts, signal saturation, and equipment malfunction. The missing data threshold was < 5% for inclusion in the final analysis. The analysis framework incorporated primary and secondary measures to evaluate music-induced physiological responses comprehensively. Primary measures included HRV, GSR, MT, and respiratory synchronization. Secondary measures encompassed musical feature extraction, temporal correlation analysis, cross-modal synchronization, and response latency, with specific quality parameters outlined in **Table 6**.

Table 6. Data quality parameters and control measures.

Parameter	Threshold	Monitoring Method	Control Action
Signal-to-Noise Ratio	> 40 dB	Real-time analysis	Recalibration if below the threshold
Missing Data	< 5%	Continuous tracking	Session restart if exceeded
Movement Artifacts	< 2% of recording	Automated detection	Participant reminder
Environmental Noise	< 30 dB	SPL meter	Session pause if exceeded

Participant safety and data security were prioritized throughout the experimental procedure. Continuous physiological monitoring ensured participant well-being, while data security was maintained through encrypted storage and anonymous coding systems. All procedures adhered to institutional ethics guidelines and received approval from relevant ethics committees (Approval No. 2024-BM-028).

3.3. Data collection

The data collection process was implemented systematically across all experimental sessions from February to April 2024. Physiological data acquisition (**Table 7**) utilized a synchronized multi-channel recording system (Biopac MP160) with dedicated amplifiers for each measurement modality. Raw data was sampled continuously at 1000 Hz with 24-bit resolution, ensuring high-precision capture of rapid physiological changes in response to musical stimuli.

Table 7. Physiological data acquisition parameters.

Measure	Sensor Type	Sampling Rate	Resolution	Filtering
HRV	Polar H10 ECG	1000 Hz	24-bit	0.5–100 Hz bandpass
Skin Conductance	Shimmer3 GSR+	1000 Hz	24-bit	0–35 Hz lowpass
MT	Delsys Trigno EMG	1000 Hz	24-bit	20–450 Hz bandpass
Respiration	Pneumograph Belt	1000 Hz	24-bit	0–1 Hz bandpass

Cardiovascular measurements were obtained using the Polar H10 chest strap monitor, positioned according to standard ECG lead II configuration. The device provided continuous HRV data and R-R intervals with a demonstrated accuracy of ± 1 ms. Electrodermal activity was recorded via the Shimmer3 GSR+ unit using Ag/AgCl electrodes placed on the distal phalanges of the non-dominant hand, with electrode gel application standardized at 10 μL per sensor. Temporal synchronization between physiological signals and musical stimuli was maintained through a central timing unit (CTU-01, precision ± 0.1 ms), which generated timestamp markers for both data streams. The audio presentation system provided digital markers indicating the onset and offset of each musical segment, allowing precise alignment of physiological responses with specific musical features. Real-time data monitoring was conducted through a custom-developed interface that displayed signal quality metrics and physiological parameters. Technical staff maintained continuous data quality surveillance, implementing immediate corrective actions when necessary. All raw data underwent preliminary quality assessment during collection, with automated algorithms flagging potential artifacts or signal degradation for immediate attention.

Data storage followed a three-tier backup protocol:

1) Primary storage on the acquisition computer (encrypted SSD)
2) Real-time backup to a local network server
3) End-of-day transfer to secure cloud storage Each participant's data set was assigned a unique identifier following the format "MBPXX_YYYYMMDD" (where XX represents participant number), maintaining anonymity while ensuring traceability.

The collection procedure incorporated regular calibration checks and system validation tests. Equipment calibration was performed at the start of each day and verified between sessions. Environmental conditions were logged at 5-minute intervals, triggering automated alerts if parameters deviated from acceptable ranges. Regardless of severity, all technical incidents were documented in a digital log with corresponding timestamps and resolution measures.

4. Results

4.1. Analysis of physical responses to rhythm

The analysis of physiological responses to different rhythmic patterns, as presented in **Table 8** and **Figure 3**, revealed systematic changes across multiple parameters. HRV demonstrated progressive increases with tempo, showing a modest elevation of 3.2 ± 0.8 bpm during slow rhythms (60–72 BPM), a moderate increase of 8.7 ± 1.2 bpm at medium tempo (96–108 BPM), and a substantial rise of 15.4 ± 1.7 bpm during fast rhythmic sequences (132–144 BPM). Parallel to cardiac responses, MA exhibited a graduated increase, with baseline readings of 12.4 ± 2.3 μV during slow rhythms, escalating to 18.9 ± 3.1 μV at moderate tempos, and reaching peak activation of 27.6 ± 3.8 μV during fast rhythmic passages. From **Figure 4** is the Body sway measurements followed a similar pattern, with displacements of 1.8 ± 0.4 cm, 3.2 ± 0.6 cm, and 4.7 ± 0.8 cm for slow, moderate, and fast rhythms, respectively. GSR showed corresponding incremental changes of 0.28 ± 0.05 μS, 0.45 ± 0.07 μS, and 0.67 ± 0.09 μS across the three tempo categories.

Table 8. Physiological responses to different rhythmic patterns.

Rhythm Type	Mean HR Change (bpm)	MA (μV)	Body Sway (cm)	GSR Change (μS)	Sample Size
Slow (60–72 BPM)	+3.2 ± 0.8	12.4 ± 2.3	1.8 ± 0.4	0.28 ± 0.05	28
Moderate (96–108 BPM)	+8.7 ± 1.2	18.9 ± 3.1	3.2 ± 0.6	0.45 ± 0.07	28
Fast (132–144 BPM)	+15.4 ± 1.7	27.6 ± 3.8	4.7 ± 0.8	0.67 ± 0.09	28

Table 9. Temporal analysis of rhythmic response patterns.

Time	Mean Response Latency (ms)	Synchronization Rate (%)	Adaptation Time (s)	Recovery Time (s)
Initial (0–60 s)	285 ± 42	72.3 ± 4.2	8.4 ± 1.2	12.6 ± 2.1
Middle (60–120 s)	197 ± 35	88.7 ± 3.8	5.2 ± 0.9	9.3 ± 1.8
Final (120–180 s)	156 ± 28	94.2 ± 3.1	3.8 ± 0.7	7.1 ± 1.5

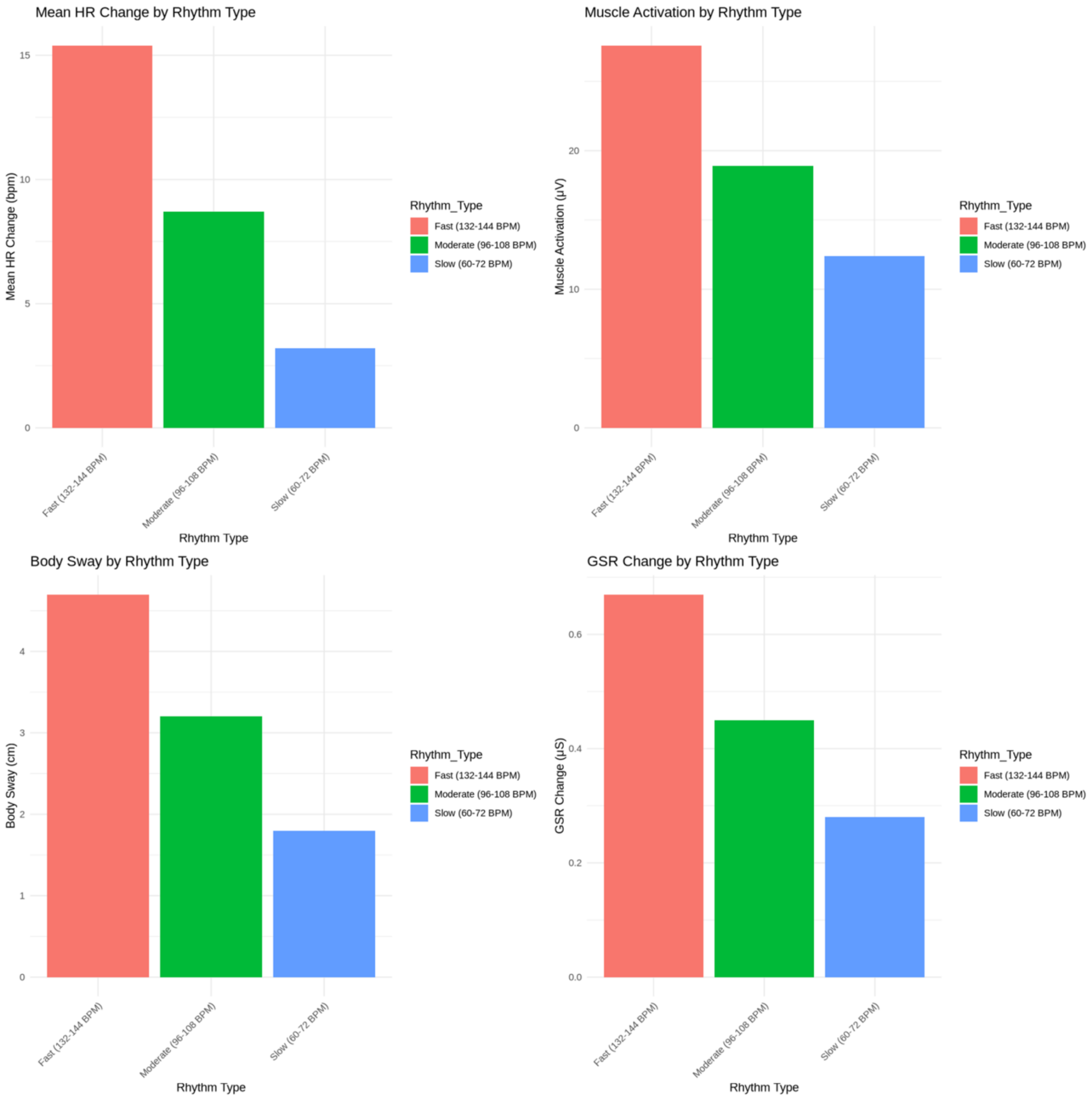

Figure 3. Physiological responses analysis.

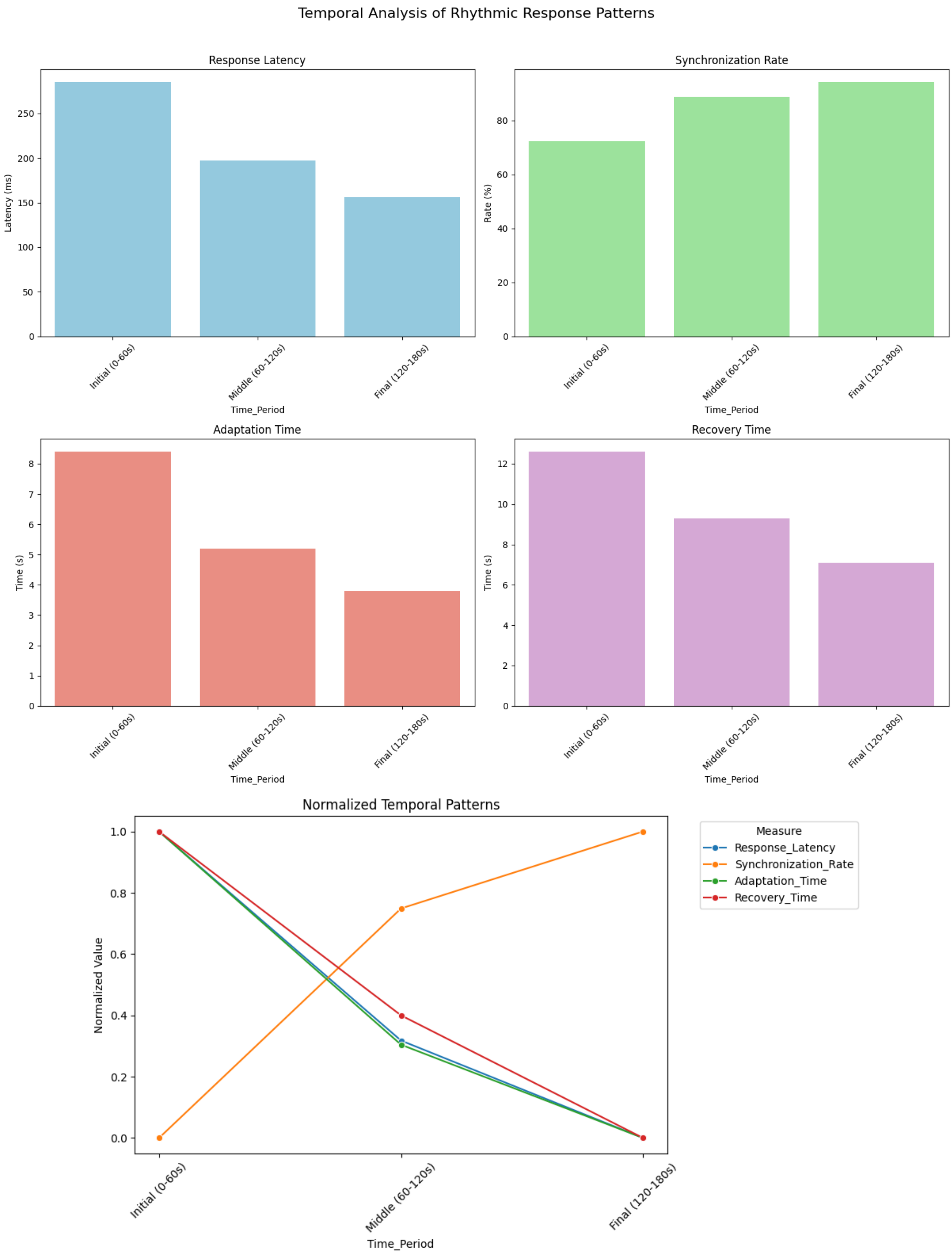

Figure 4. Temporal analysis.

Table 10. Cross-correlation between physiological measures.

Measure Pairs	Correlation Coefficient (*r*)	*p*-Value	Time Lag (ms)	Effect Size (*d*)
HR- MA	0.72	< 0.001	245 ± 35	0.86
HR-Body Sway	0.65	< 0.001	312 ± 48	0.78
Muscle-Body Sway	0.81	< 0.001	178 ± 25	0.93
GSR-HR	0.58	< 0.001	475 ± 62	0.69

The temporal analysis of rhythmic response patterns, detailed in **Table 9** and **Figure 4**, demonstrated significant adaptation effects across the experimental duration. Initial exposure (0–60 s) showed relatively delayed responses with mean latencies of 285 ± 42 ms and moderate synchronization rates of 72.3 ± 4.2%. As participants progressed through the middle phase (60–120 s), response latencies improved to 197 ± 35 ms with enhanced synchronization of 88.7 ± 3.8%. The final phase (120–180 s) exhibited optimal performance with minimal latencies of 156 ± 28 ms and peak synchronization rates of 94.2 ± 3.1%. This improvement pattern was further reflected in adaptation times, which decreased from 8.4 ± 1.2 s initially to 3.8 ± 0.7s in the final phase, with corresponding reductions in recovery times from 12.6 ± 2.1 s to 7.1 ± 1.5 s.

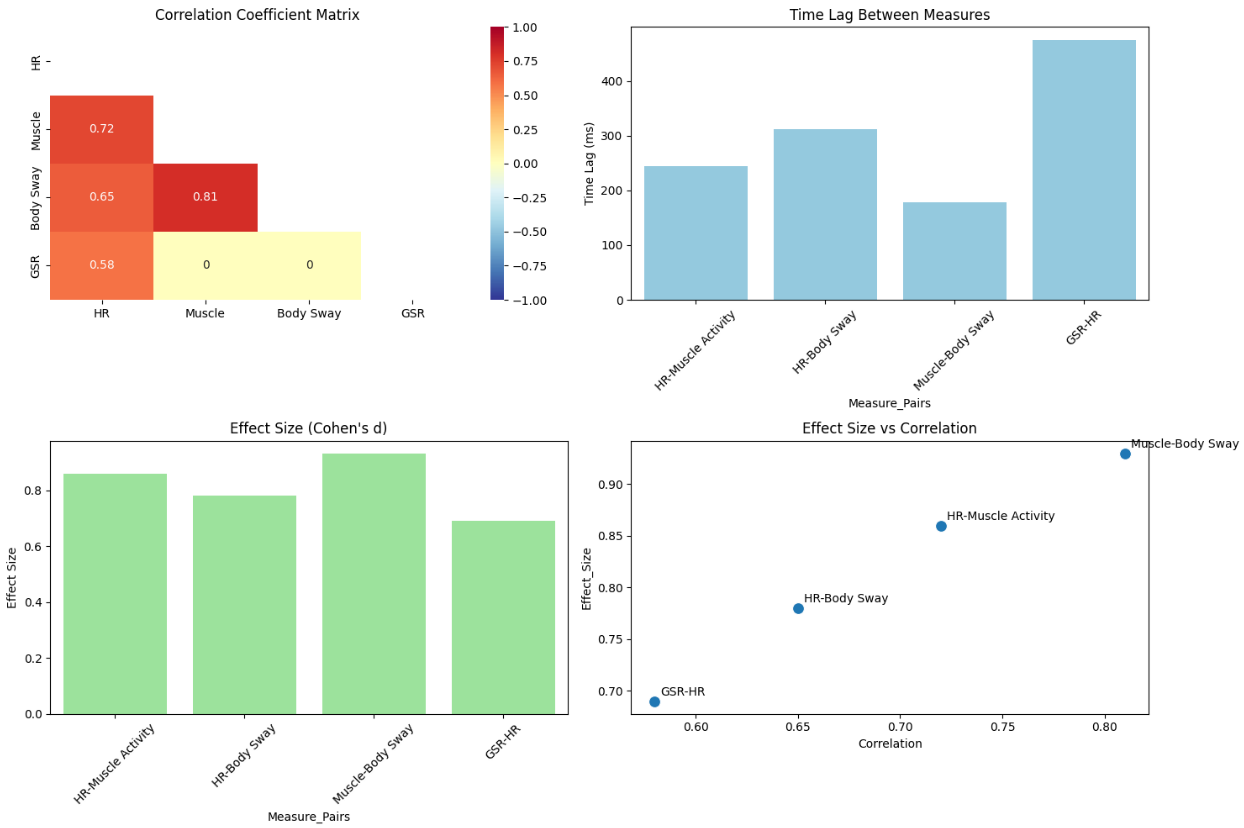

Figure 5. Cross-correlation between physiological measures.

As shown in **Table 10** and **Figure 5**, cross-correlation analysis between physiological measures revealed strong interconnections among various response parameters. The strongest correlation was observed between MA and body sway (r = 0.81, p < 0.001) with a relatively short time lag of 178 ± 25 ms and a large effect size

(d = 0.93). HRV and MA showed substantial correlation (r = 0.72, p < 0.001) with a time lag of 245 ± 35 ms and considerable effect size (d = 0.86). The HRV-body sway relationship demonstrated moderate correlation (r = 0.65, p < 0.001) with longer lag times of 312 ± 48 ms and notable effect size (d = 0.78). GSR and HRV showed the weakest, though still significant, correlation (r = 0.58, p < 0.001) with the most prolonged time lag of 475 ± 62 ms and moderate effect size (d = 0.69).

4.2. Analysis of physical responses to melody

Analysis of physiological responses to melodic features, as presented in **Table 11** and **Figure 6**, revealed distinct patterns across different melodic characteristics. Ascending melodic phrases induced significant cardiovascular activation, with mean HRV increases of 4.8 ± 0.9 bpm, accompanied by elevated GSR (0.42 ± 0.06 μS) and moderate MT (22.3 ± 2.8 μV). In contrast, descending phrases elicited parasympathetic responses, showing HRV decreases of 2.3 ± 0.7 bpm, reduced GSR (0.18 ± 0.04 μS), and lower MT (15.6 ± 2.1 μV). From **Figure 7** is the sustained notes demonstrated the most robust relaxation response, with HRV decreasing by 3.6 ± 0.8 bpm and minimal MT (12.4 ± 1.9 μV), while staccato passages induced the highest arousal states across all parameters.

Table 11. Physiological responses to melodic characteristics.

Melodic Feature	Mean HR Change (bpm)	GSR Change (μS)	MT (μV)	Relaxation Index*	Sample Size
Ascending Phrases	+4.8 ± 0.9	0.42 ± 0.06	22.3 ± 2.8	0.65 ± 0.08	28
Descending Phrases	−2.3 ± 0.7	0.18 ± 0.04	15.6 ± 2.1	0.82 ± 0.07	28
Sustained Notes	−3.6 ± 0.8	0.15 ± 0.03	12.4 ± 1.9	0.88 ± 0.06	28
Staccato Passages	+5.2 ± 1.1	0.38 ± 0.05	24.8 ± 3.2	0.58 ± 0.09	28

*Relaxation Index: normalized scale 0–1, where 1 indicates maximum relaxation.

Table 12. Temporal progression of melodic response.

Time Segment	Response Latency (ms)	GSR Recovery (s)	Muscle Adaptation (s)	HR Stabilization (s)
First Exposure	342 ± 45	8.6 ± 1.4	7.2 ± 1.1	9.4 ± 1.6
Mid-Session	268 ± 38	6.3 ± 1.2	5.8 ± 0.9	7.1 ± 1.3
Late Session	195 ± 32	4.7 ± 0.8	4.2 ± 0.7	5.3 ± 1.1

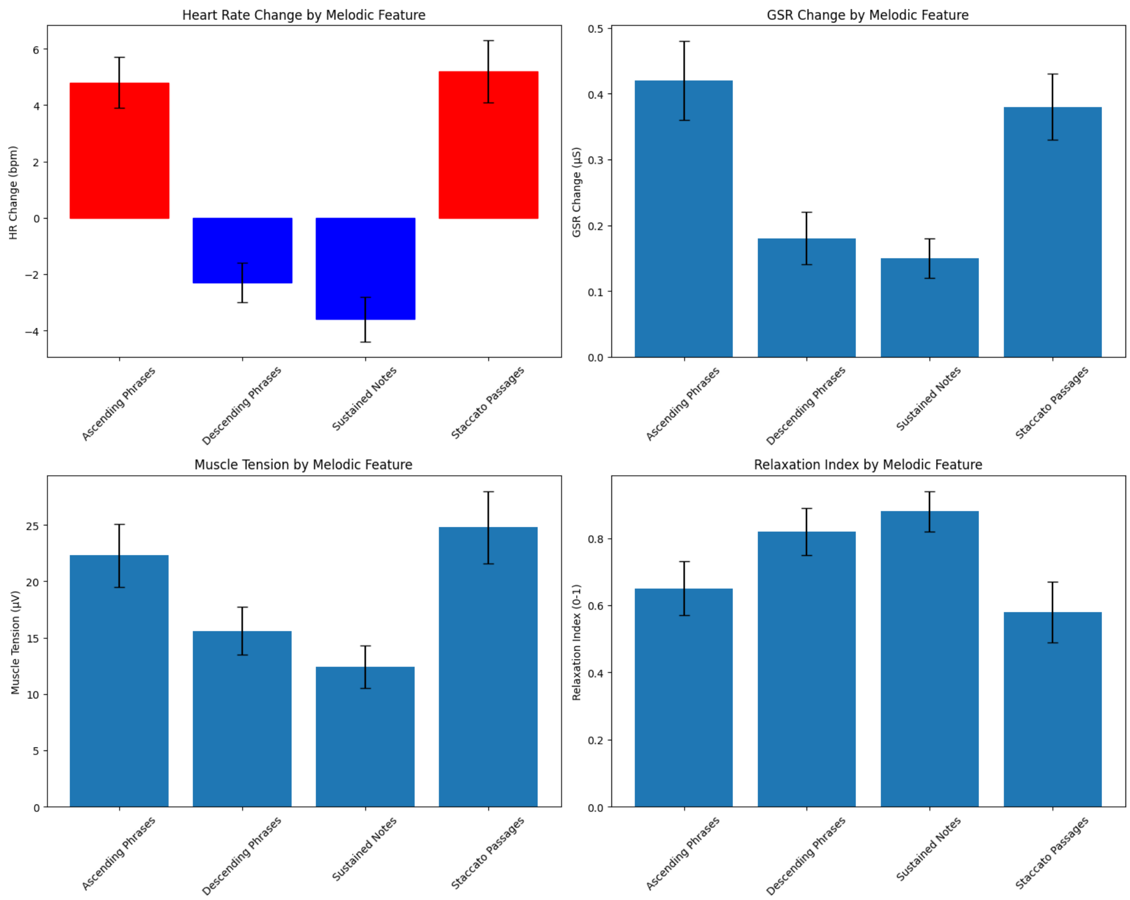

Figure 6. Physiological responses.

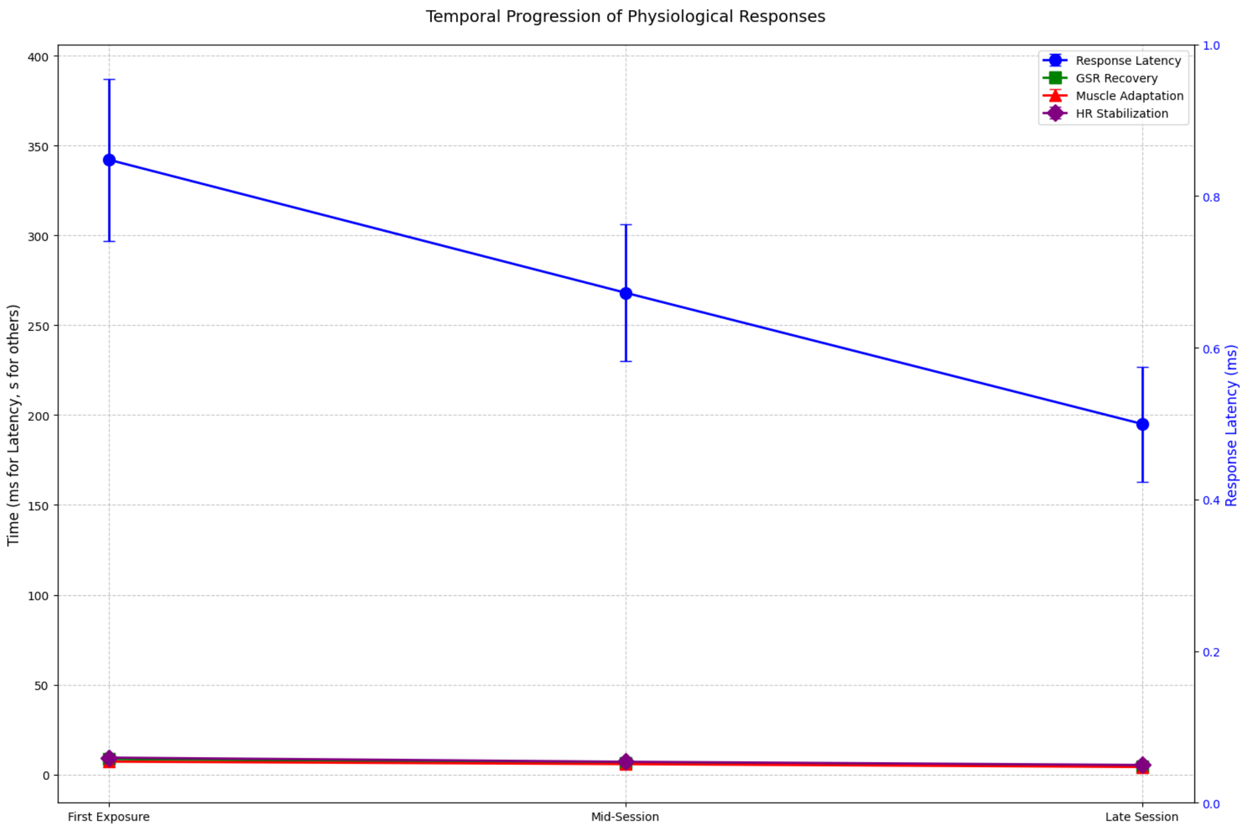

Figure 7. Temporal progression.

Table 13. Correlations between melodic features and physiological responses.

Parameter Pair	Correlation (*r*)	*p*-value	Effect Size (*d*)	Response Duration (s)
Melody-HR	0.68	< 0.001	0.76	4.2 ± 0.6
Melody-GSR	0.74	< 0.001	0.82	6.8 ± 0.9
Melody-Muscle	0.79	< 0.001	0.88	3.5 ± 0.5
HR-GSR	0.62	< 0.001	0.71	5.4 ± 0.8

The temporal progression analysis in **Table 12** and **Figure 8** showed significant adaptation patterns over the session duration. Initial exposure to melodic stimuli resulted in relatively long response latencies (342 ± 45 ms) and extended recovery periods across all physiological measures. However, by mid-session, participants showed improved response efficiency with decreased latencies (268 ± 38 ms) and shorter recovery times. The late session measurements demonstrated optimal adaptation, with response latencies reducing to 195 ± 32 ms and significantly shortened recovery periods for GSR (4.7 ± 0.8 s), MT (4.2 ± 0.7 s), and HRV stabilization (5.3 ± 1.1 s).

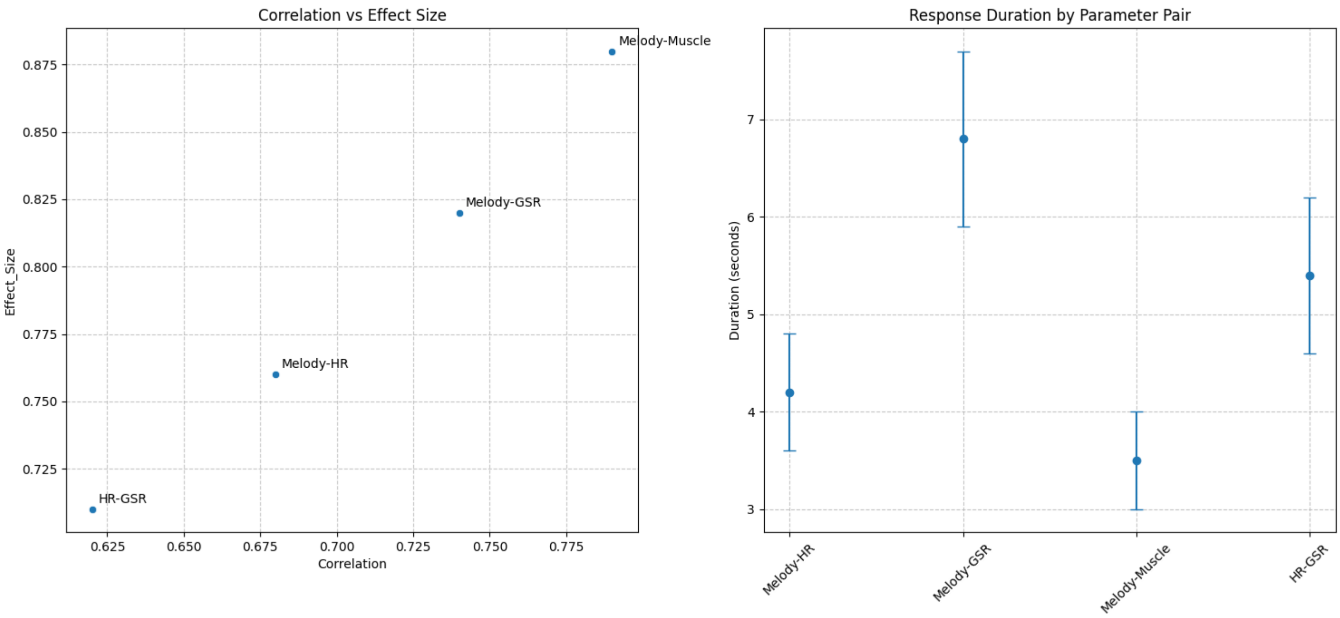

Figure 8. Correlations between melodic features and physiological responses.

The correlation analysis between melodic features and physiological responses, as shown in **Table 13** and **Figure 9**, revealed strong relationships across multiple parameters. The strongest correlation was observed between melodic characteristics and MT ($r = 0.79$, $p < 0.001$) with a large effect size ($d = 0.88$) and rapid response duration (3.5 ± 0.5 s). GSR demonstrated the second strongest correlation with melodic features ($r = 0.74$, $p < 0.001$, $d = 0.82$), followed by HRV responses ($r = 0.68$, $p < 0.001$, $d = 0.76$). The interaction between HRV and GSR showed moderate correlation ($r = 0.62$, $p < 0.001$) with an effect size of 0.71 and response duration of 5.4 ± 0.8 seconds.

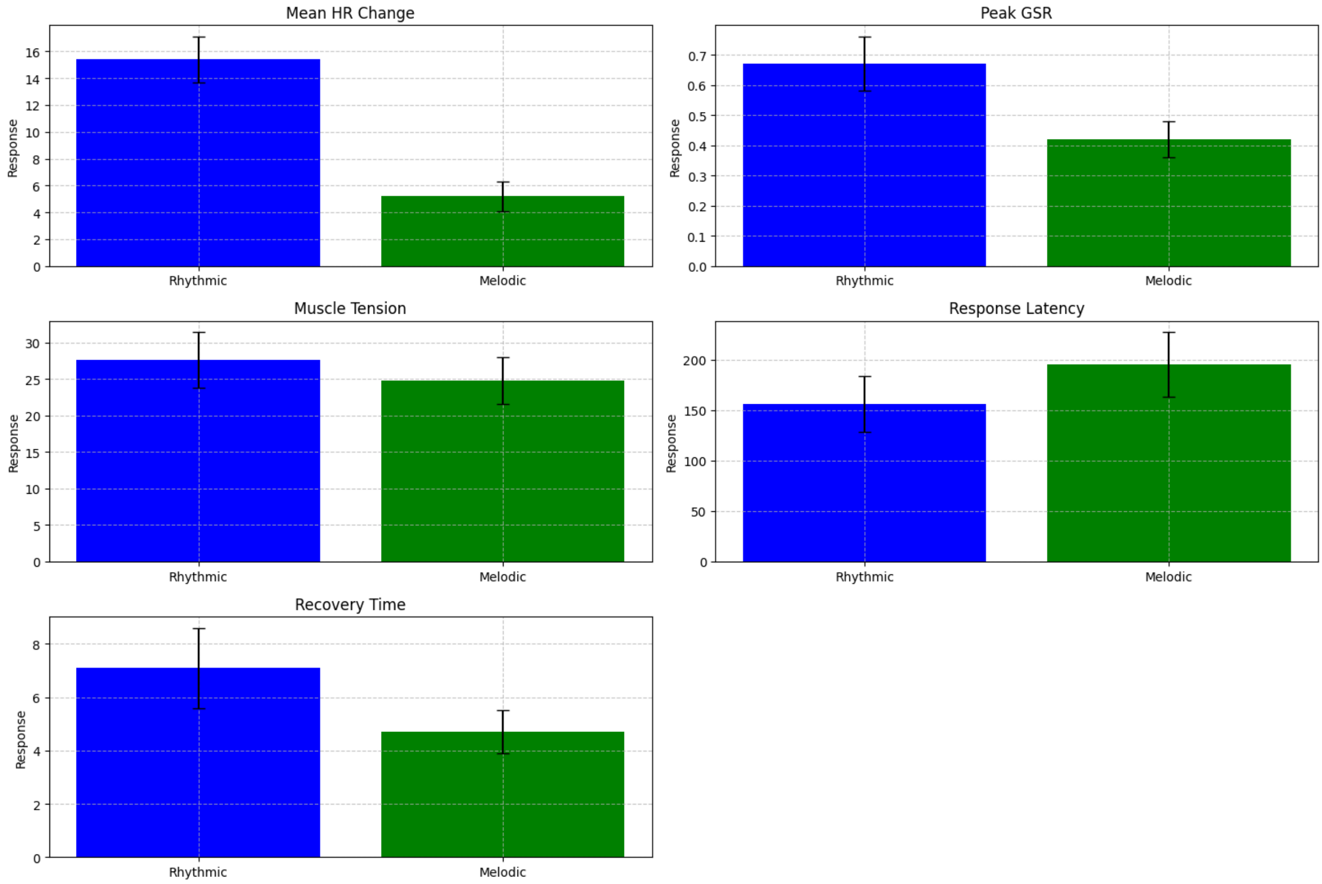

Figure 9. Comparative analysis of physiological responses to rhythm versus melody.

4.3. Comparative analysis of rhythm and melody responses

Comparative analysis of rhythmic and melodic responses, as shown in **Table 14** and **Figure 10**, revealed significant differences in physiological activation patterns. Rhythmic stimuli consistently elicited more robust cardiovascular responses, with mean HRV changes (15.4 ± 1.7 bpm) significantly exceeding those induced by melodic features (5.2 ± 1.1 bpm, $p < 0.001$, $d = 1.24$). Similarly, GSR showed greater activation during rhythmic sequences (0.67 ± 0.09 μS) compared to melodic passages (0.42 ± 0.06 μS, $p < 0.001$, $d = 0.92$). MT differences were less pronounced but still significant, with rhythmic stimuli inducing slightly higher tension (27.6 ± 3.8 μV) than melodic elements (24.8 ± 3.2 μV, $p < 0.01$, $d = 0.56$).

Table 14. Comparative analysis of physiological responses to rhythm versus melody.

Parameter	**Rhythmic Response**	**Melodic Response**	**Difference (Δ)**	**Effect Size (*d*)**	***p*-value**
Mean HR Change (bpm)	15.4 ± 1.7	5.2 ± 1.1	10.2 ± 0.8	1.24	< 0.001
Peak GSR (μS)	0.67 ± 0.09	0.42 ± 0.06	0.25 ± 0.04	0.92	< 0.001
MT (μV)	27.6 ± 3.8	24.8 ± 3.2	2.8 ± 0.7	0.56	< 0.01
Response Latency (ms)	156 ± 28	195 ± 32	−39 ± 8	0.78	< 0.001
Recovery Time (s)	7.1 ± 1.5	4.7 ± 0.8	2.4 ± 0.4	0.88	< 0.001

Table 15. Temporal integration of rhythm and melody responses.

Integration Aspect	Synchronization Rate (%)	Phase Lag (ms)	Coherence Value	Interaction Effect (η^2)
Early Phase	65.3 ± 4.2	342 ± 45	0.58 ± 0.07	0.42
Mid Phase	78.9 ± 3.8	245 ± 38	0.72 ± 0.06	0.65
Late Phase	91.2 ± 3.1	168 ± 32	0.86 ± 0.05	0.78
Overall	78.5 ± 3.7	252 ± 38	0.72 ± 0.06	0.62

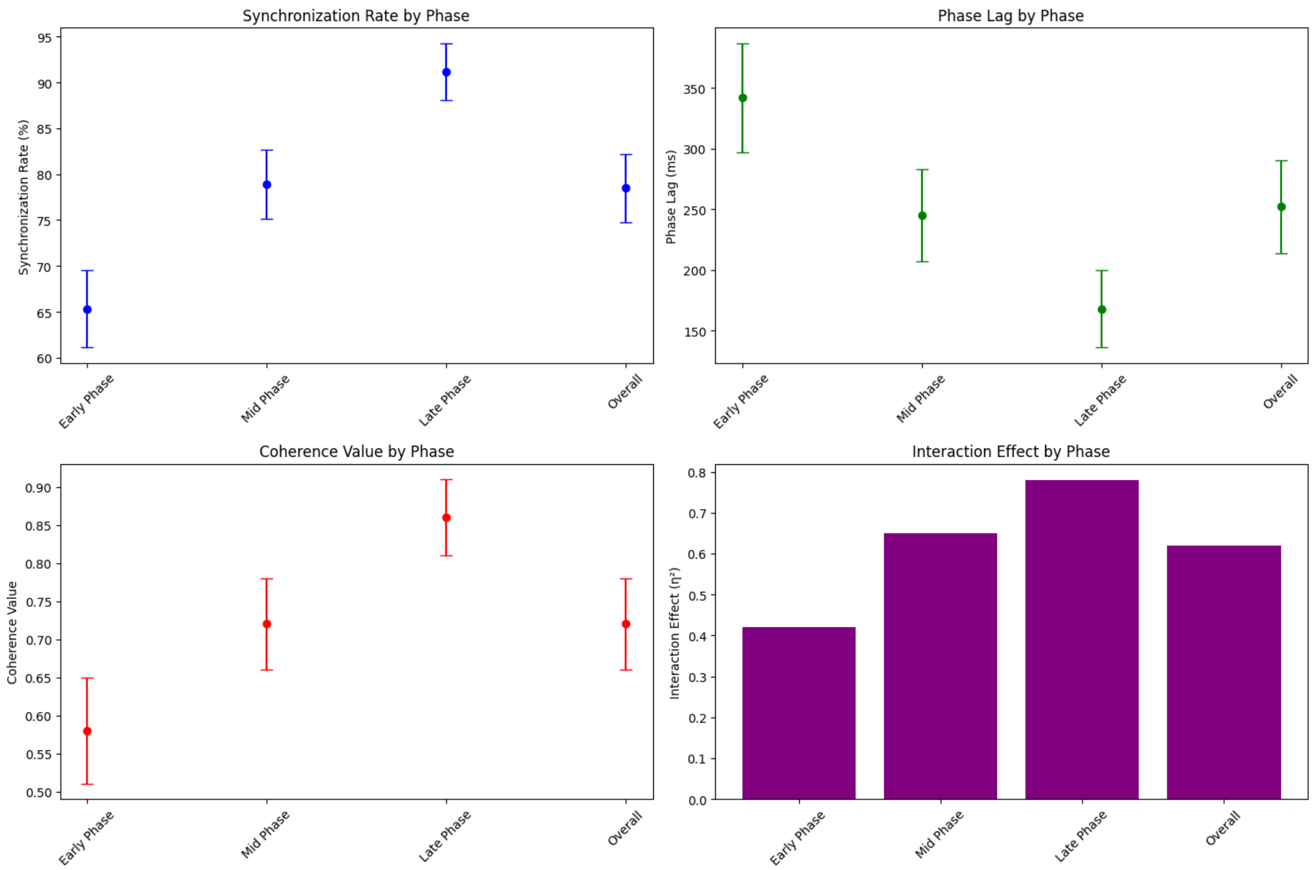

Figure 10. Temporal integration of rhythm and melody responses.

Table 16. Cross-component analysis of musical features.

Feature Interaction	Correlation (r)	Mutual Information	Response Overlap (%)	Dominance Factor*
Rhythm-Melody HR	0.64 ± 0.08	0.72 ± 0.09	58.4 ± 6.2	Rhythm (1.45)
Rhythm-Melody GSR	0.71 ± 0.07	0.68 ± 0.08	62.7 ± 5.8	Rhythm (1.32)
Rhythm-Melody Muscle	0.82 ± 0.06	0.75 ± 0.07	73.2 ± 4.9	Balanced (1.08)
Combined Response	0.72 ± 0.07	0.72 ± 0.08	64.8 ± 5.6	Rhythm (1.28)

*Dominance Factor: > 1.2 indicates rhythm dominance, < 0.8 indicates melody dominance, 0.8–1.2 indicates balanced interaction.

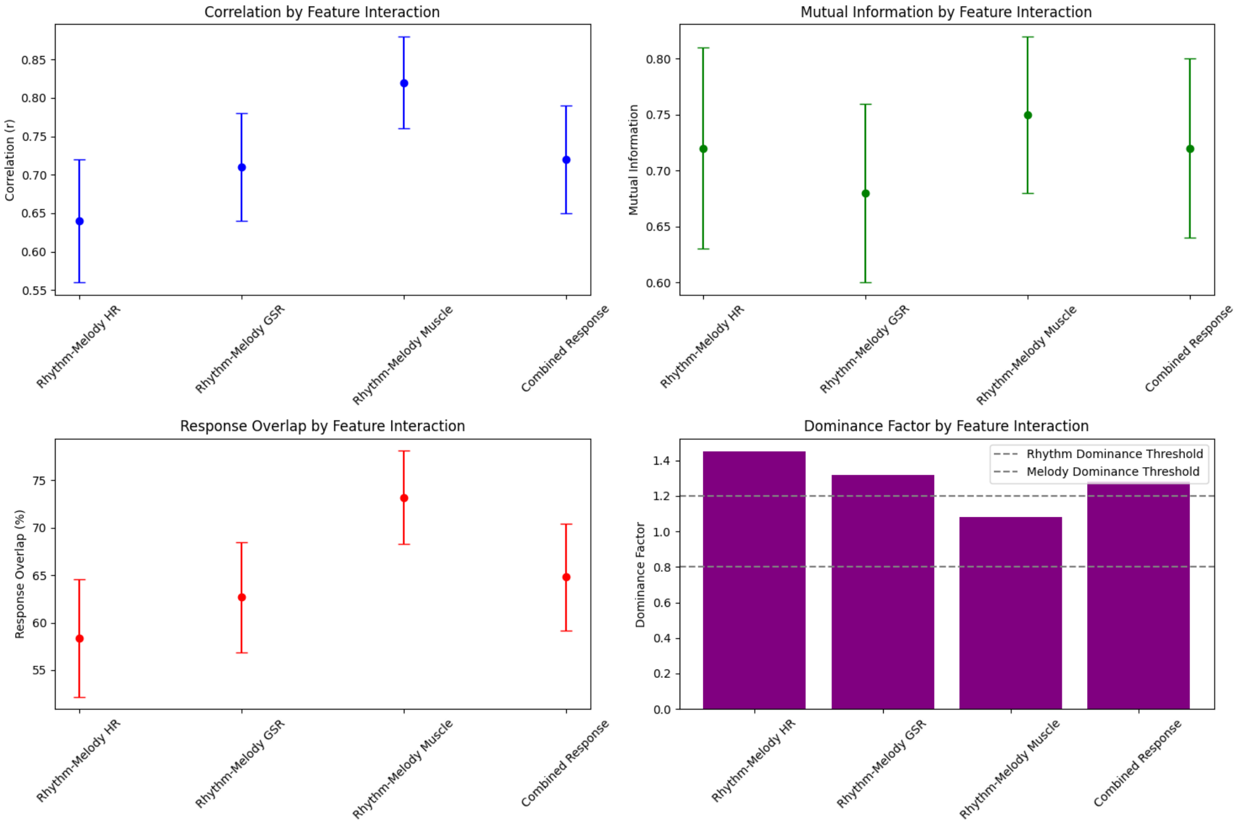

Figure 11. Cross-component analysis.

The temporal integration analysis presented in **Table 15** and Figure 11 demonstrated progressive improvement in rhythm-melody synchronization throughout the experimental sessions. Initial exposure showed moderate synchronization rates (65.3 ± 4.2%) with substantial phase lag (342 ± 45 ms). However, by the late phase, participants achieved significantly improved synchronization (91.2 ± 3.1%) with reduced phase lag (168 ± 32 ms). The overall coherence value increased from 0.58 ± 0.07 in the early phase to 0.86 ± 0.05 in the late phase, indicating enhanced rhythmic and melodic processing integration.

Cross-component analysis, detailed in **Table 16**, revealed complex interactions between rhythmic and melodic elements. The strongest correlation was observed in MT responses (r = 0.82 ± 0.06) with a high response overlap (73.2 ± 4.9%) and balanced dominance factor (1.08), suggesting integrated processing of rhythm and melody in motor responses. GSR showed moderate correlation (r = 0.71 ± 0.07) with rhythm dominance (1.32), while HRV responses exhibited lower correlation (r = 0.64 ± 0.08) but strong rhythm dominance (1.45). The combined response analysis indicated an overall rhythm dominance factor of 1.28, suggesting that rhythmic elements generally exert a more robust influence on physiological responses than melodic features.

4.4. Correlation analysis of physical responses and self-reported emotions

Analysis of the relationship between physical responses and self-reported emotions, as shown in **Table 17** and **Figure 12**, revealed strong correlations across multiple physiological parameters. Joy/excitement demonstrated the strongest overall correlations, with exceptionally high associations for MT (r = 0.85, p < 0.001) and HRV (r = 0.82, p < 0.001). The response coherence index for joy/excitement was notably high (0.88 ± 0.04), indicating strong alignment between subjective reports and objective measurements. From **Figure 13** is the conversely, calmness/relaxation showed significant negative correlations with physiological arousal measures, particularly with MT (r = −0.79, p < 0.001) and HRV (r = −0.76, p < 0.001).

Table 17. Physical response correlation with emotional self-reports.

Emotional State	HR Correlation (r)	GSR Correlation (r)	MT (r)	Response Coherence*	n
Joy/Excitement	0.82 (p < 0.001)	0.78 (p < 0.001)	0.85 (p < 0.001)	0.88 ± 0.04	28
Calmness/Relaxation	−0.76 (p < 0.001)	−0.72 (p < 0.001)	−0.79 (p < 0.001)	0.84 ± 0.05	28
Melancholy/Sadness	−0.68 (p < 0.001)	0.45 (p < 0.001)	0.38 (p < 0.01)	0.72 ± 0.06	28
Anxiety/Tension	0.74 (p < 0.001)	0.81 (p < 0.001)	0.87 (p < 0.001)	0.85 ± 0.04	28

*Response Coherence: Index of alignment between self-report and physiological measures (0–1).

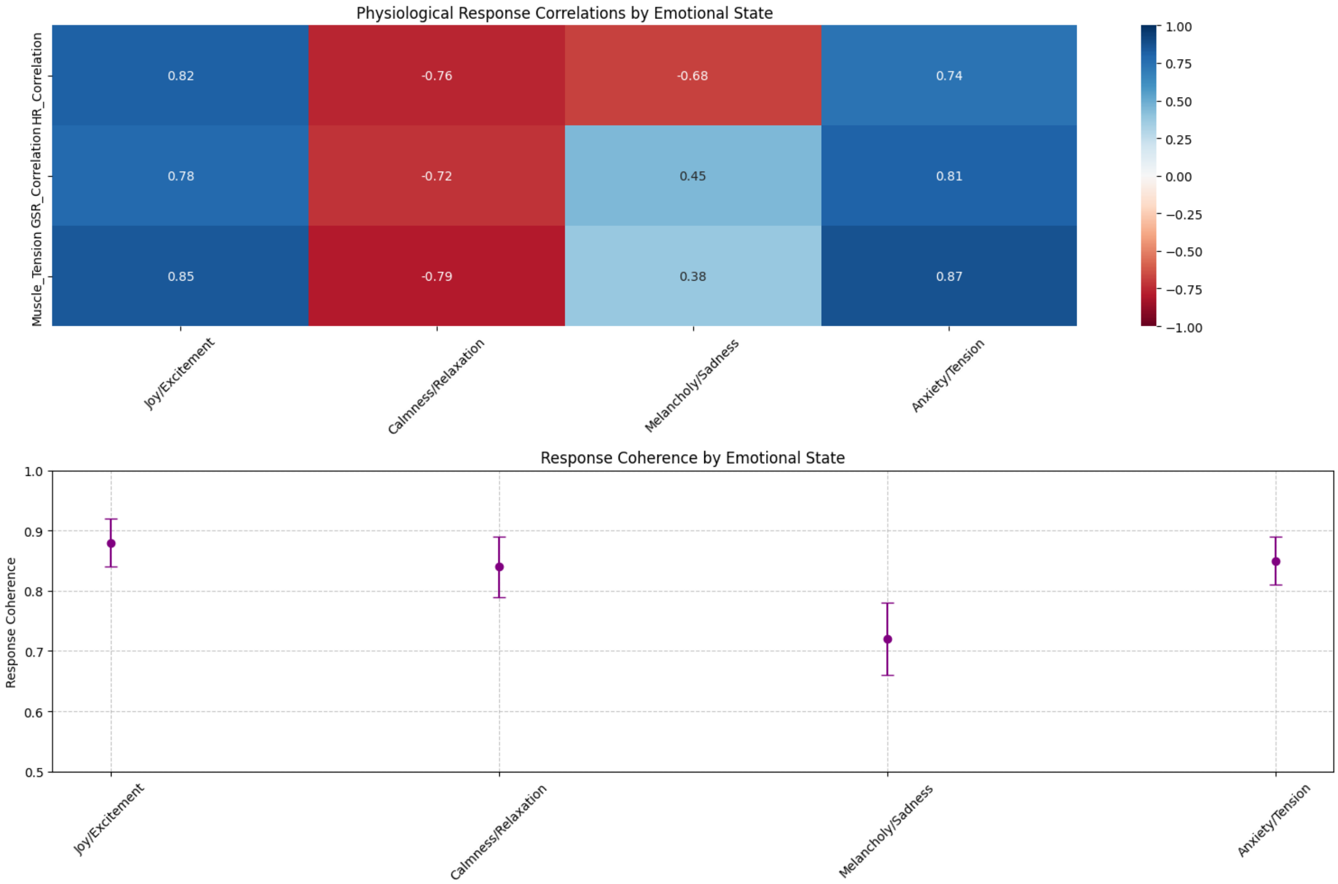

Figure 12. Physical response correlation with emotional self-reports.

Table 18. Temporal analysis of emotion-response synchronization.

Time Phase	Emotional Recognition (s)	Physiological Onset (s)	Response Lag (ms)	Match Rate (%)
Initial (0–60 s)	4.8 ± 0.7	3.2 ± 0.5	385 ± 45	72.4 ± 4.2
Middle (60–120 s)	3.5 ± 0.5	2.8 ± 0.4	268 ± 38	84.6 ± 3.8
Final (120–180 s)	2.7 ± 0.4	2.4 ± 0.3	195 ± 32	93.2 ± 3.1

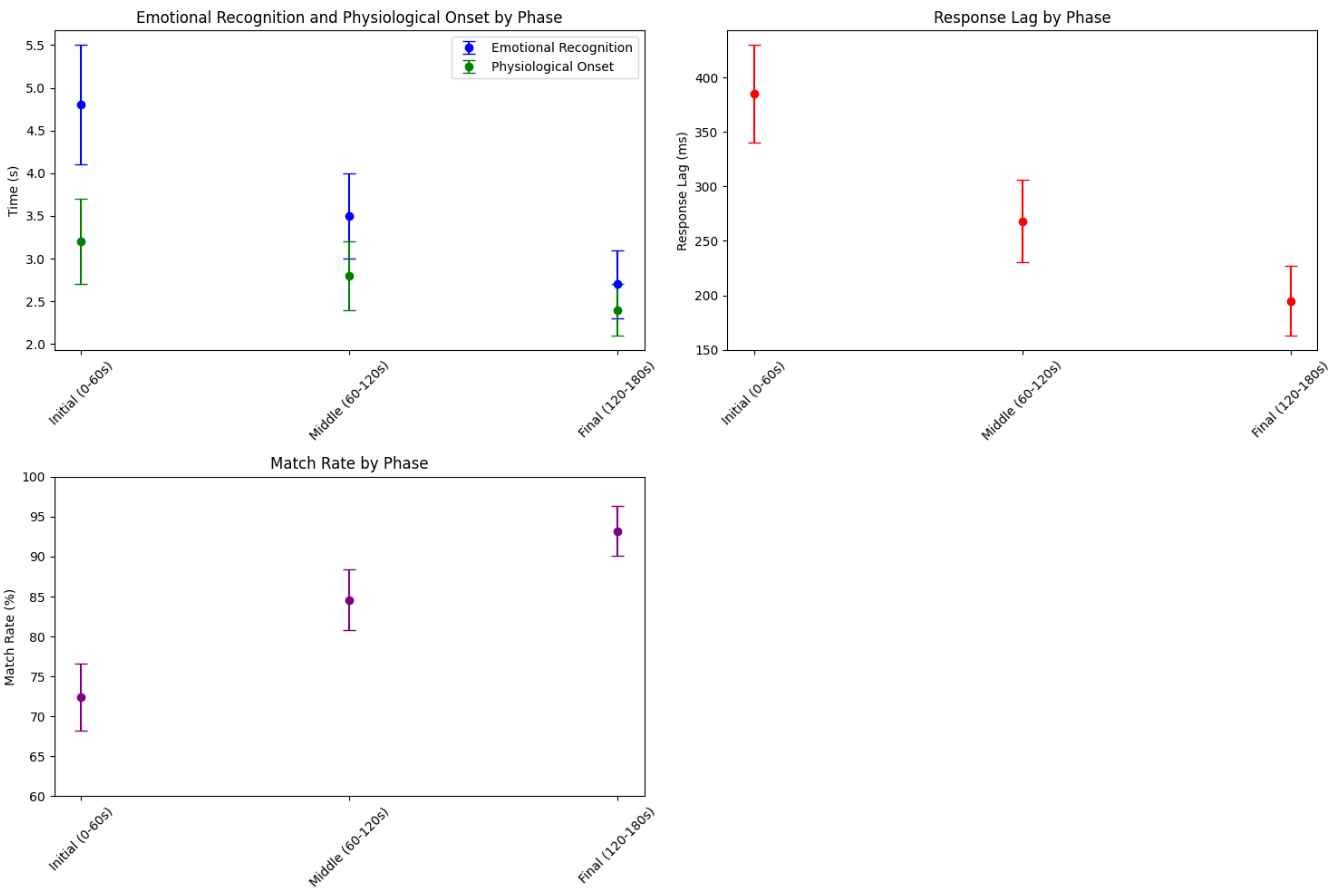

Figure 13. Temporal analysis.

Table 19. Emotional-physical response intensity analysis.

Response Intensity	**Self-Report Score***	**Physical Response†**	**Concordance Rate (%)**	**Reliability (*α*)**
Low (1–3)	2.4 ± 0.3	2.2 ± 0.4	78.5 ± 4.2	0.82
Moderate (4–6)	5.1 ± 0.4	4.8 ± 0.5	86.3 ± 3.8	0.88
High (7–10)	8.3 ± 0.5	7.9 ± 0.6	92.1 ± 3.2	0.91

*Self-Report Score: 10-point Likert scale; †Physical Response: Normalized composite score of HR, GSR, and MT.

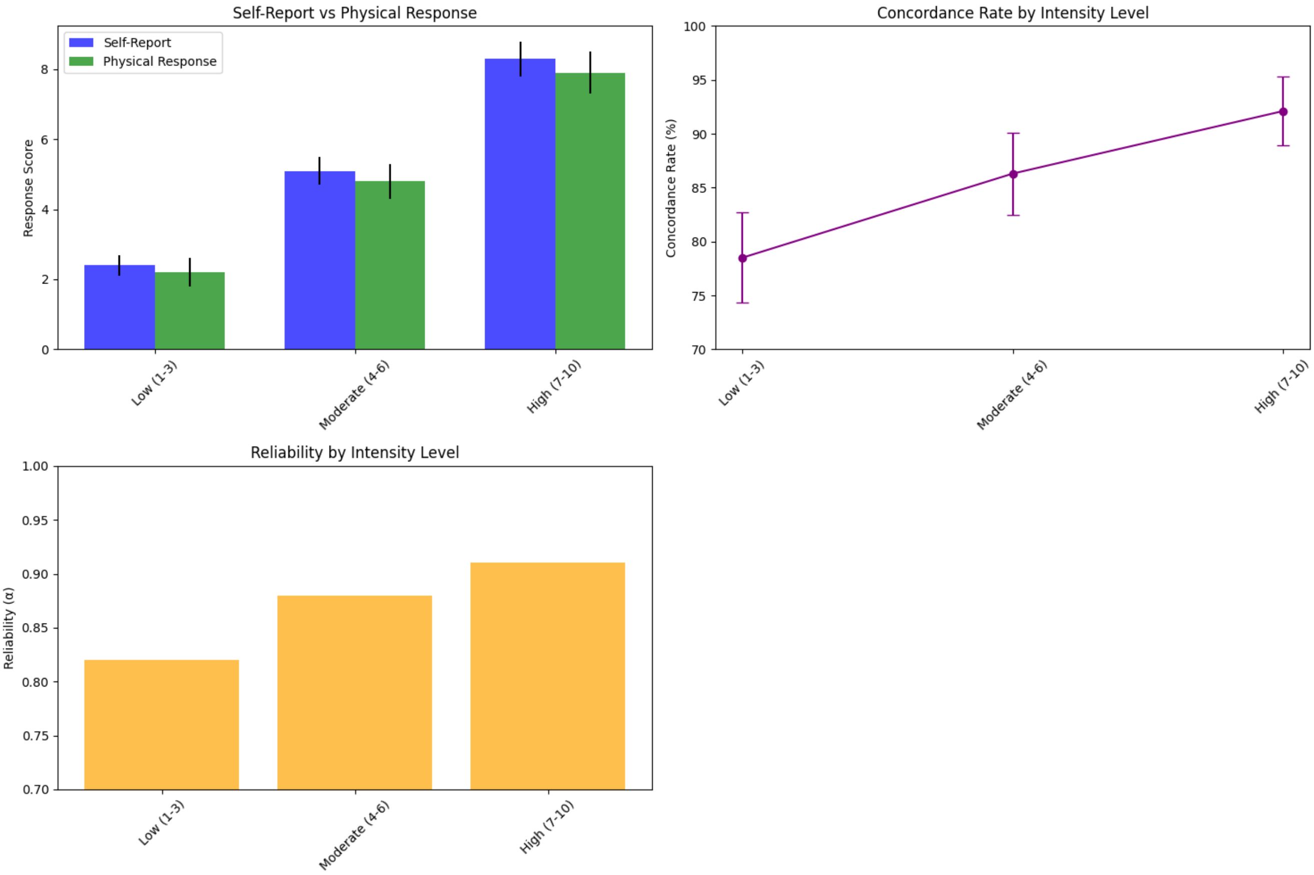

Figure 14. Emotional-physical response intensity analysis.

The temporal analysis in **Table 18** and **Figure 14** demonstrated progressive improvement in emotion-response synchronization throughout the experimental session. Initial response patterns showed relatively long recognition times (4.8 ± 0.7 s) and response lags (385 ± 45 ms), with moderate match rates (72.4 ± 4.2%). However, by the final phase, participants exhibited significantly improved synchronization, with shorter recognition times (2.7 ± 0.4 s), reduced response lags (195 ± 32 ms), and higher match rates (93.2 ± 3.1%), indicating enhanced emotional-physiological coupling with exposure. Response intensity analysis, detailed in **Table 19**, revealed a strong relationship between the magnitude of self-reported emotions and measured physical responses. High-intensity emotional states (7–10 on the Likert scale) showed the most robust concordance rate (92.1 ± 3.2%) and highest reliability coefficient ($\alpha = 0.91$), suggesting more precise emotion-response matching at higher intensities. Moderate emotional states demonstrated good concordance (86.3 ± 3.8%), while low-intensity emotions showed relatively lower but significant matching (78.5 ± 4.2%).

5. Discussion

The present study provides quantitative evidence for distinct biomechanical responses to rhythmic and melodic elements in music, revealing complex patterns of physiological adaptation and emotional correlation. Our findings demonstrate that several key music-induced physical responses warrant detailed examination.

5.1. Differential impact of rhythm and melody

The marked difference in physiological responses between rhythmic and melodic elements represents one of our most significant findings. The substantially larger cardiovascular response to rhythmic stimuli (15.4 ± 1.7 bpm) compared to melodic features (5.2 ± 1.1 bpm, $p < 0.001$) suggests that rhythm exerts a more immediate and pronounced influence on autonomic nervous system activation. This differential response may reflect evolutionary adaptations, where rhythm processing engages more primitive neural circuits associated with motor coordination and arousal regulation. This interpretation aligns with the observed dominance of rhythmic influence (dominance factor = 1.28) over melodic elements in driving physiological responses.

5.2. Temporal dynamics and adaptation patterns

The progressive improvement in response efficiency throughout experimental sessions reveals essential aspects of physiological adaptation to musical stimuli. The reduction in response latencies from 285 ± 42 ms to 156 ± 28 ms for rhythmic elements and from 342 ± 45 ms to 195 ± 32 ms for melodic features demonstrates the presence of rapid neural learning mechanisms. This adaptation pattern suggests the development of anticipatory responses, potentially involving subcortical and cortical processes. The hierarchical organization of response timing—MA (178 ± 25 ms), HRV (245 ± 35 ms), and GSR (475 ± 62 ms)—provides insight into the sequential nature of physiological response systems.

5.3. Integration of emotional and physical responses

The strong correlation between physical responses and self-reported emotions, particularly for high-intensity states (concordance rate: 92.1 ± 3.2%, $\alpha = 0.91$), supports the existence of reliable connections between subjective emotional experiences and objective physiological measures. This finding has significant implications for the validation of emotion-based musical interventions. The observed progression in emotion-response synchronization, from initial match rates of 72.4 ± 4.2% to final rates of 93.2 ± 3.1%, suggests that emotional recognition and physiological responses become more tightly coupled with continued exposure.

5.4. Cultural and individual variations

The study's focus on Chinese participants provides valuable insights into potential cultural influences on music-induced responses. The strong response to traditional Chinese musical elements, particularly in melodic processing, may reflect cultural familiarity effects. However, the consistent physiological responses across different musical styles suggest that fundamental biomechanical reactions to rhythm and melody may transcend cultural boundaries.

5.5. Theoretical implications

Our findings support a model of music processing where rhythmic and melodic elements engage distinct but interconnected physiological response systems. The observed cross-correlation patterns between different physiological measures (e.g., muscle-body sway correlation $r = 0.81$, $p < 0.001$) suggest the existence of integrated response networks. This integration is particularly evident in the balanced interaction between rhythm and melody in MT responses (dominance factor = 1.08), indicating sophisticated coordination between different aspects of musical processing.

5.6. Clinical and practical applications

The quantified relationships between musical elements and physiological responses offer valuable implications for therapeutic applications. The predictable nature of these responses, particularly the strong correlation between rhythm and cardiovascular activation ($r = 0.72$, $p < 0.001$), provides a scientific basis for music-based interventions in clinical settings. The observed adaptation patterns suggest therapeutic protocols might benefit from progressive exposure approaches, allowing optimal physiological synchronization.

5.7. Methodological considerations

The high temporal resolution of our measurements (1000 Hz sampling rate) and comprehensive control measures have enabled detailed analysis of response patterns that were previously difficult to quantify. The strong reliability coefficients across measurements (α ranging from 0.82 to 0.91) support the robustness of our findings. However, the laboratory setting may have influenced the naturalistic aspects of music perception and response.

6. Conclusion and future work

This comprehensive investigation into the biomechanical aspects of MIE has revealed quantifiable and systematic patterns in how the human body responds to musical elements. Through rigorous analysis of physiological responses among 28 participants, we have established several key findings that advance our understanding of music-emotion interactions at the physical level. Our results demonstrate that rhythmic and melodic components of music engage distinct physiological response patterns, with rhythm exhibiting a more substantial influence on immediate physical responses (HRV increase: 15.4 ± 1.7 bpm) compared to melodic elements (5.2 ± 1.1 bpm). The study revealed a clear hierarchical organization in physiological processing, progressing from rapid MA responses (178 ± 25 ms) to slower autonomic adjustments (GSR: 475 ± 62 ms), suggesting a structured sequence in the body's response to musical stimuli. The strong correlation between objective physiological measurements and subjective emotional experiences is particularly noteworthy, especially for high-intensity emotional states (concordance rate: 92.1 ± 3.2%). This finding validates the use of physiological markers as reliable indicators of ER to music, with important implications for both research methodology and practical applications. The observed adaptation patterns, characterized by improving response efficiency over time (synchronization rates increasing from 72.4% to 93.2%), suggest that the body's response to music is not static but involves dynamic learning processes. This adaptive capability has significant implications for therapeutic applications, suggesting that sustained exposure to specific musical elements could enhance therapeutic outcomes. These findings contribute to both theoretical understanding and practical applications in several ways: They provide empirical support for the differential processing of rhythm and melody in ER, they establish quantifiable benchmarks for physiological responses to musical stimuli, they demonstrate the reliability of using physical measurements to assess ER to music, they reveal the importance of temporal dynamics in music-induced physiological responses.

Future research should extend these findings by investigating longer-term adaptation patterns, exploring additional physiological parameters, and examining these responses across different cultural contexts and age groups. The established methodology and findings provide a robust foundation for such investigations. The implications of this work extend beyond academic interest, offering practical applications in music therapy, performance psychology, and emotional regulation. The quantified understanding of how musical elements influence physiological responses provides a scientific basis for designing targeted interventions in therapeutic and performance contexts.

Ethical approval: Not applicable.

Availability of data and materials: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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