Psychophysiological Correlates of Emotion During Music Perception

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***Abstract*— Emotional experiences during music listening are supported by dynamic interactions between perceptual, cognitive, and physiological processes, yet the extent to which bodily responses reflect or predict music-induced emotions remains an open question. In this preliminary study, we aimed to investigate the relationship between music listening enjoyment and a variety of physiological responses, testing whether any subset of these measures can be used to predict music-induced emotions. We presented each participant with obscure instrumental music excerpts, recorded several physiological responses during music listening, and asked them to subjectively rate their experienced valence (positive to negative affect) and arousal (high to low energy). Using an exploratory structural equation model, we found that high-frequency heart rate variability (HF HRV), skin conductance levels (SCL), and respiration rate had small yet significant correlations with arousal, while HF HRV and the range of skin conductance responses (SCR) were correlated with valence. These findings indicate that physiological responses like SCR and respiration rate could potentially serve as an objective measure of music-induced emotions, though the low predictive power of the model necessitates more expansive confirmatory analyses. Future research should expand upon these findings through larger sample sizes, cluster models, and by more closely investigating the influence of internal state.**

Keywords*— *Music listening, arousal, valence, subjective ratings, emotional responses, psychophysiology, physiology

I. Introduction

Listening to music is one of the most enjoyable and emotionally rich experiences in which people engage. Unlike other rewarding activities, music does not fulfill an obvious biological need or resemble fundamental drives such as eating or social bonding; however, people frequently seek out music for the pleasure it brings and the genuine emotions it can evoke [1–3]. These musical emotions—such as happiness, sadness, and fear—can be identified universally [2]. While it is widely acknowledged that music can evoke strong affective states, the specific relationship between emotional changes during listening and the pleasurable aspects of the experience remains underexplored.

Previous studies have explored whether emotional state can be reliably indicated by physiological responses to music [4–6]. Two dimensions can be used to describe emotion: valence and arousal. Valence refers to how positive or negative an emotion is, where happiness and calm are classified as positively valenced emotions, and sadness and anger are classified as negatively valenced [7]. Valence is typically assessed through self-reported emotional ratings, such as through the Self-Assessment Manikin (SAM) [8]. Arousal reflects the level of physiological or emotional activation a person experiences, where happiness and anger are high arousal emotions, and sadness and calm are low arousal emotions [7]. Like valence, arousal can be self-reported but is also frequently measured using physiological indicators such as heart rate, which reflect the body's autonomic nervous system activity [9–11].

While subjective emotional ratings remain a key measure, more objective physiological indicators such as heart rate (BPM), electrodermal activity (EDA), and respiration (RSP) have been increasingly used to determine whether these responses can predict emotional states during music listening [12, 13]. Some studies have found that EDA, specifically SCL, was positively correlated with happy music, but not with sad music [5, 14]. These studies also found no effect of BPM, with Lundqvist et al. [14] finding that both types of music triggered a pattern of initial slowing followed by speeding up of BPM. The researchers interpreted this pattern as an orienting response, suggesting that it reflected a shift in the participants' attention toward the music. Other studies report a positive linear relationship between BPM and valence, especially in the context of "musical chills" [12, 15, 16]. This seems to be contrary to the general emotion literature, in which people experience faster BPMs in the presence of strong negative valence, and a weaker relationship with positive valence [17]. Other music studies have found a strong positive relationship between RSP rate and valence [12], skin conductance responses (SCR) and arousal [18], and SCL with valence and arousal [12, 19, 20].

Fast-tempo music is often associated with feelings of excitement or high arousal, while slower tempos are usually associated with calmer, lower arousal states. These differences in rhythm can have a strong effect on how we emotionally interpret what we hear [21]. Our bodies often adjust in response to music. For instance, changes in heart rate or breathing may reflect the tempo or intensity of a song (e.g., [22]). This adjustment is partly driven by a mechanism in which the brain processes rhythmic patterns in music and relays signals to various organs, such as the heart. These signals modulate physiological responses; faster musical

tempos are typically associated with increased pulse rate and blood pressure, while slower tempos tend to produce the opposite effect [23]. This physical reaction can inform our emotional experience, potentially amplifying the feelings expressed in music [24, 25]. When we respond emotionally to happy or sad music, it is not just about whether the music feels positive or negative—the structure of the music itself, especially elements like tempo and rhythm, could also play a big role. Subconscious autonomic responses were identified for both respiratory and cardiovascular parameters that were consistent across all participants, regardless of their musical preferences or prior training [26]. In prior research [26], musical profile was closely reflected in changes in the skin's microvasculature, suggesting a potential subconscious link between auditory stimuli and cardiovascular responses. This implies that the subjective experience of a "chill" may depend on whether the intensity of these cardiovascular changes surpasses a certain threshold, allowing them to enter conscious awareness.

In this study, we investigated whether a systematic relationship exists between certain physiological measurements (i.e., heart function, skin-conductance, and respiration) and behavioral reports of music-induced emotion (i.e. valence and arousal) in previously unexperienced music. By incorporating physiological data into the study of music listening, we aim to better understand how internal states shape emotional responses to music and to broaden the multisensory perspective of music cognition. These findings may offer an alternative to subjective, behavioral measures of emotion and may help us distinguish between the perceptual and cognitive effects of music on emotion. The results can allow us to partially bridge the gap between science and experience by judging implicit appraisals (physiology) in conjunction with explicit ones (subjective ratings).

II. Materials and methods

II-A. Dataset

All studies were approved by the North General Institutional Review Board (IRB) of the University of California, Los Angeles (UCLA). All of the participants were UCLA undergraduate students who were recruited through the UCLA Psychology Subject Pool. They were compensated with course credit for their participation in the study. The data were collected anonymously, and each participant had normal hearing. Demographic information (i.e., age, gender, and ethnicity) was not collected, as it did not have relevance to our hypotheses. Informed consent for research and publication was obtained from all individuals prior to experimentation. To prevent potential biases, participants were not briefed on the study's hypothesis but only about the respective tasks. Thirty-five students participated in the study, but five participants' data were removed on account of technological errors. One more participant was removed from the data analysis for having a baseline average heart rate that was three standard deviations above the mean (122 BPM). This resulted in the inclusion of 29 participants in the study.

II-B. Study Design

After signing the consent form, we asked participants to wear headphones and focus on a fixation cross in the center of the computer screen for the duration of the experiment. We used a BIOPAC MP160 and wireless BioNomadix monitors to collect electrocardiogram (ECG), EDA, photoplethysmography (PPG), and RSP measurements from the participants at a sampling rate of 2000 Hz (every half millisecond). ECG is measured in microVolts (μV), EDA in microsiemens (μS), PPG in volts, and RSP in volts. We also used the AcKnowledge Data Acquisition and Analysis Software to process and save the raw data. The experiment consisted of three repeating stages.

1) *Baseline Trial:* Participants listened to white noise for 45 seconds. This acted as the baseline condition, which allowed us to collect initial baseline physiology and allowed participant physiology to return to baseline levels between each music presentation.
2) *Experimental Trial:* Participants listened to a music excerpt that was between 45 and 60 seconds long.
3) *Response Trial:* Participants were asked to report their subjective induced valence and arousal on the computer in the form of Likert Scales ranging $\pm$100 for each dimension. They were also asked to click a check box if they knew the song they had just heard.

This was repeated 28 times, once for each of the 28 songs included in the experiment. The order of the songs was randomized.

II-C. Song Excerpt Criteria

In this study, we were interested in the perceptual influences of music on emotion, rather than the cognitive ones. Previous studies of music-induced emotion used popular songs as stimuli, which were often familiar to the participant and contained lyrics [7]. These songs have cognitive associations that could shift one's interpretation of a piece of music, and thus the emotions they feel when listening to it. To avoid this potential cognitive bias, we established a strict procedure for song selection. Firstly, we scoured previous studies to find songs that were validated as inducing emotion, to give us a foundation for the study. Out of three papers [1, 7, 27], we collected 179 songs. To establish whether they were obscure, we used Google Trends to compare the song to an incredibly popular song in the United States and abroad ("Yellow Submarine"

by the Beetles). If the song of choice was below the 25% threshold, then we considered it "obscure" enough for experimentation. This resulted in a sublist of 76 songs. According to a previous study [28], 45 seconds to 60 seconds of music listening is necessary to induce emotion. This is also similar to Khalfa et al.[5], who had participants listen to one-minute music clips. Using this as our guide, we extracted 45-to-60 seconds-long song excerpts that did not include lyrics. Some of the selected songs did not have instrumental sections that were long enough, reducing our song list further to 45 songs of varying genres. Finally, we wanted to have an equal number of songs in each category of valence and arousal pairings: Positive Valence & High Arousal (PV-HA), Negative Valence & High Arousal (NV-HA), Positive Valence & Low Arousal (PV-LA), Negative Valence & Low Arousal (NV-LA). We also wanted to limit the experiment to one hour, so as to reduce participant fatigue. This resulted in 7 songs per category and 28 songs total.

II-D. Pre-processing and Data Preparation

Prior to data analysis, all trials in which participants indicated that they knew the song were removed from the analysis. This resulted in the exclusion of 12 experimental, baseline, and response trials out of 812, resulting in 800 analyzed trials. All data were initially analyzed using the NeuroKit2 package (version 0.2.11) in Python (version 3.11.9). We used the default parameters from the **_process* functions in NeuroKit2 for filtering, artifact criteria, and resampling [29]. The documentation can be found here. Per experimental and baseline trial, we calculated the average heart rate (BPM), time-domain analysis of heart rate variability (Root Mean Square of Successive Differences; RMSSD HRV), frequency-domain analysis of heart rate variability (High Frequency; HF HRV), tonic EDA (or SCL), phasic EDA (or SCR), area under the curve of phasic EDA, range of phasic EDA, RSP rate, RSP amplitude, and PPG. We did not analyze the response trials given their exceedingly short durations. Some experimental and baseline trials had incomplete data, particularly for RSP measurements. This is likely due to improper attachment of electrodes during data collection. This reduced the trials to 761 experimental trials of RSP rate, 789 experimental trials of RSP amplitude, 799 baseline trials of HF HRV, 755 baseline trials of RSP rate, and 795 baseline trials of RSP amplitude. All other measurements retained all 800 experimental trials and 800 baseline trials.

III. Results

III-A. Baseline Validity

To determine whether physiology returned to baseline levels during each baseline trial, we conducted an array of pairwise t-tests comparing the initial baseline to the average of all subsequent baselines, per measurement. Using the conservative Bonferroni correction (α = 0.005), we find that none of the measures are significantly different between the initial baseline and the subsequent baseline trials (see Table 1); however, RMSSD HRV (t = 2.277, p = 0.031), HF HRV (t = 2.073, p = 0.048), and tonic EDA (t = 2.378, p = 0.024) should be interpreted with caution, as they would be significant without the comparisons correction. All other physiological measurements can be safely interpreted.

Table 1. Pairwise t-test results comparing the initial and subsequent baseline trials across participants. Values in **bold** are significant under Bonferroni corrections, where α = 0.005, and underlined values would be significant if Bonferroni corrections were not used, where α = 0.05.

Measurement	t-value	p-value
BPM	-1.160	0.256
RMSSD HRV	2.277	0.031
HF HRV	2.073	0.048
EDA Tonic	2.378	0.024
EDA Phasic	1.017	0.318
EDA Phasic AUC	1.417	0.167
EDA Phasic Range	-0.763	0.452
RSP Rate	1.105	0.280
RSP Amplitude	-1.643	0.112
PPG	-1.222	0.232

III-B. Experimental Analysis

The relationship between physiological measurements and subjective emotional ratings can be expressed as a latent variable model (see Figure 1). In this model, Physiology predicts Subjective Experience, where the physiological measurements load on to the Physiology latent variable and the subjective ratings of valence and arousal load on to the Subjective Experience latent variable. The heart rate measurements covary since they are recorded from the same channel (ECG), as are the EDA measurements and the RSP measurements. For the current data structure, the model should also be a three-level model, as the data are clustered within song (level 2) and within participant (level 3).

Unfortunately, neither a model with latent variables nor multiple levels can converge, as there is not enough data in the present sample to produce sufficient power. We instead developed an exploratory model by first analyzing the measurements from each physiological channel separately. This resulted in four models containing ECG-only, EDA-only, RSP-only, and PPG-only, regressed onto arousal and valence directly. All four models had great model fit, though they are just-identified, as is indexed by the CFI, RMSEA, and SRMR values (see Table 2). According to BIC, EDA and PPG were the top performers.

Each of the models had some measurements that significantly predicted valence and arousal and some that did not (see Table 3). As an exploratory step, we created a single model that combines the significant measure-

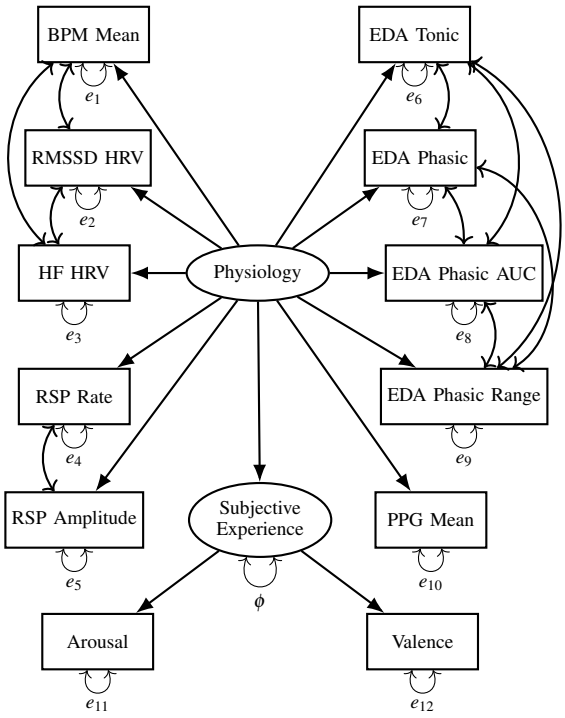

Figure 1. Proposed path model illustrating the relationship between physiological measurements and reports of subjective emotional experience during music listening. Clustering by participant and by song is not visible in the model.

Table 2. Fit statistics for each of the four individual physiology models. All of the models are just-identified.

Model	CFI	RMSEA	SRMR	BIC
ECG-only	1.000	<0.001	<0.001	31681.231
EDA-only	1.000	<0.001	<0.001	16957.495
RSP-only	1.000	<0.001	<0.001	23757.859
PPG-only	1.000	<0.001	<0.001	16949.281

ments from across the four models (see Figure 2). This model has the best fit for the data so far ($\chi^2(4)$ = 2.903, p = 0.574, CFI = 1.000, $RMSEA$ < 0.001, $SRMR$ = 0.012, BIC = 16113.650). The regression results show multiple small yet significant standardized effects across measurements, suggesting that musically-induced emotions are correlated with biological responses from across the body. HF HRV (β = 0.090, p = 0.013), EDA tonic (β = 0.075, p = 0.025), and RSP rate (β = 0.100, p = 0.003) were all significantly correlated with arousal. In the composite model, PPG was only marginally significantly correlated with valence (β = -0.064, p = 0.059), potentially due to collinearity or instability; however, HF HRV (β = 0.085, p = 0.021), and the range of phasic EDA (β = 0.158, p < .001) were still correlated with valence scores. Despite these relationships, the variance explained for arousal (R^2 = 0.024, 95% CI [0.009, 0.051]) and valence (R^2 = 0.036, 95% CI [0.019, 0.070]) is very small. Arousal and valence are also positively correlated (r = 0.413, p < 0.001).

Table 3. Standardized regression coefficients and p-values for all predictors across the four initial physiology models. Values in **bold** are statistically significant ($p < 0.05$) and were later included in the composite model.

Measurement	Arousal	p-value	Valence	p-value
BPM	-0.031	0.470	-0.045	0.300
RMSSD HRV	-0.057	0.199	-0.029	0.514
HF HRV	**0.091**	**0.016**	**0.079**	**0.037**
EDA Tonic	**0.104**	**0.004**	0.040	0.262
EDA Phasic	-0.564	0.293	-0.991	0.062
EDA Phasic AUC	0.623	0.245	0.957	0.072
EDA Phasic Range	-0.033	0.432	**0.165**	**<0.001**
RSP Rate	**0.133**	**<0.001**	0.019	0.621
RSP Amplitude	0.055	0.141	0.039	0.304
PPG	-0.024	0.493	**-0.080**	**0.023**

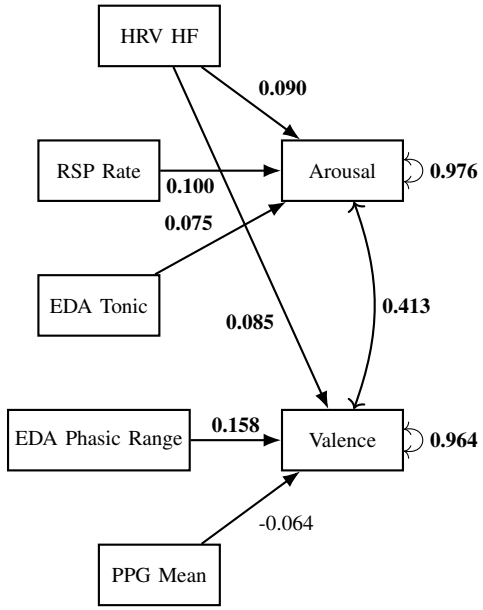

Figure 2. Composite model. Path values (labeling single-headed arrows) represent standardized regression coefficients. Values in **bold** are statistically significant (p < .05). Residual variances (double-headed arrow pointing at a singular measurement) and covariances (double-headed arrow connecting two measurements) are also visible.

It is important to note that the composite model treats all trials as independent observations, despite the multilevel data structure. Given the likelihood of an increased Type 1 error due to assuming observation independence, we also decided to calculate intraclass correlations (ICCs) per measurement to estimate the amount of variance due to clustering that was unaccounted for in the non-clustered model (see Table 4). The ICCs indicate strong clustering within participants for all physiological measurements (e.g., HF HRV, etc.), but moderate to weak clustering for subjective emotional reports (i.e., Valence and Arousal). Contrarily, there was

strong clustering within trials for the subjective reports, but weak clustering for the physiological measurements.

Table 4. ICCs for composite model measurements for both the participant level (Level 3) and song level (Level 2) clusters.

Measurement	Level 3 ICC	Level 2 ICC
Arousal	0.027	0.328
Valence	0.074	0.221
HF HRV	0.296	0.024
EDA Tonic	0.858	0.003
EDA Phasic Range	0.332	<0.001
RSP Rate	0.539	0.014
PPG	0.852	0.002

III-C. Internal State Relationship

Another point of interest in this experiment is the influence of internal state on physiology during music listening. In this case, internal state refers to the physiological state of a participant prior to experimentation, as recorded in the initial baseline. Since the baseline trials are not significantly different from one another, we can use them in this analysis. We tested whether participant physiology in these baseline trials was predictive of physiology in subsequent experimental trials using a linear mixed model (LMM). Each physiology measurement during the baseline trials was significantly predictive of the respective physiological measurement scores in subsequent experimental trials (see Table 5). The fixed effects are also very large, with EDA Tonic having the strongest relationship ($\beta = 0.949$, $p < 0.001$).

Table 5. LMM of Prior Baseline Trial and Subsequent Experimental Trial. Values in **bold** are significant.

Variable	Fixed Effects	Standard Error	p-value
BPM	**0.656**	0.035	**<0.001**
RMSSD HRV	**0.237**	0.029	**<0.001**
HF HRV	**0.224**	0.039	**<0.001**
EDA Tonic	**0.949**	0.010	**<0.001**
EDA Phasic	**0.485**	0.032	**<0.001**
EDA Phasic AUC	**0.499**	0.032	**<0.001**
EDA Phasic Range	**0.697**	0.021	**<0.001**
RSP Rate	**0.148**	0.039	**<0.001**
RSP Amplitude	**0.561**	0.029	**<0.001**
PPG	**0.344**	0.031	**<0.001**

IV. Discussion

These results imply that the examined physiological responses play a small yet significant role in musically-induced valence and arousal ratings. In the composite model, we observed that some physiological measurements like HRV HF, RSP rate, and EDA tonic, are significantly predictive of arousal scores, while HRV HF and EDA phasic range are significantly predictive of valence scores. Given that this model was exploratory and was not able to account for latent variables or multilevel clustering, future experiments should collect more data in order to test the relationship between physiology and subjective reporting under a complete multilevel latent variable model. The ICCs imply strong participant level clustering effects for the physiological measures, and strong song level effects for subjective reporting, so we expect a multilevel structural equation model to produce different results than our exploratory model. Future experiments could also expand the duration of baseline trials, as many other studies have done [5, 12, 14–16, 19, 20], collect a more diverse and generalizable sample of participants than our current homogeneous sample (i.e., undergraduate students), and collect additional demographic information such as musical experience to use as a covariate.

Some of our findings were inconsistent with prior studies, as we found a positive relationship between RSP Rate and arousal, rather than valence [12] and between a measure of phasic EDA and valence, rather than arousal [18]. This may be attributed to the high correlation between valence and arousal during music listening. Unlike emotional ratings during visual perceptual pleasure, there was a linear relationship between valence and arousal, rather than a parabolic one [17]. This is likely because music is created to be enjoyed, so music that elicits fear (low valence, high arousal) is uncommon or lacking in this dataset. Further, it is intuitive that RSP would be tied to high arousal, given the relationship between heart rate, breathing, and arousal [9–11]. The significant relationship between arousal and RSP rate implies a potential relationship between BPM and arousal as well, even though that is not evidenced in the current analysis. For the EDA relationship, we suggest that valence may influence phasic activity indirectly, via mechanisms such as motivational salience, attentional capture, or contextual expectancy.

The internal state analysis offers new perspectives on the relationship between music-induced emotions and physiology. For instance, there is a strong relationship between baseline measurements of EDA Phasic Range and measurements of EDA Phasic Range during music listening. EDA Phasic Range also exhibits a successful return to baseline across baseline trials and is significantly correlated with Valence. Future experiments could investigate whether there is an influence of prior internal state on the relationship between physiology during music listening and subjective emotional responses, although it is beyond the scope of the current paper to make any claims as to its influence.

V. Conclusions

This preliminary study implies that the physiological measurements collected here have the potential to be used as a tool for measuring music-induced emotion, even if they do not fully explain why music induces emotional responses. These physiological measurements are best predictive of subjective emotional responses when addressed in combination, rather than individually, giving us a more wholistic understanding of the relationship between physiology and emotion. Further,

prior internal state may affect the way humans respond to emotion-inducing music. Another interesting relationship that could be explored in future studies is the impact of specific song features on physiology and subjective emotional ratings [30]. Future studies should continue to focus on the role of physiology in the music-emotion relationship, perhaps including additional physiological measures such as EEG, so that we may better understand the mechanisms behind the emotional power of music.

REFERENCES

[1] D. Västfjäll, "Emotion induction through music: A review of the musical mood induction procedure," *Musicae Scientiae*, vol. 5, no. 1, pp. 173–211, 2002.

[2] T. Fritz, S. Jentschke, N. Gosselin, D. Sammler, I. Peretz, R. Turner, A. D. Friederici, K. E. Stephan, and S. Koelsch, "Universal recognition of three basic emotions in music," *Current Biology*, vol. 19, no. 7, pp. 573–576, Mar 2009.

[3] H. Egermann, N. Fernando, L. Chuen, and S. McAdams, "Music induces universal emotion-related psychophysiological responses: Comparing canadian listeners to congolese pygmies," *Frontiers in Psychology*, vol. 5, no. 1341, pp. 1–9, 2015.

[4] C. L. Krumhansl, "An exploratory study of musical emotions and psychophysiology," *Canadian Journal of Experimental Psychology*, vol. 51, pp. 336–353, 1997.

[5] S. Khalfa, M. Roy, P. Rainville, S. D. Bella, and I. Peretz, "Role of tempo entrainment in psychophysiological differentiation of happy and sad music," *International Journal of Psychophysiology*, vol. 68, pp. 17–26, 2008.

[6] M. Iwanaga, A. Kobayashi, and C. Kawasaki, "Heart rate variability with repetitive exposure to music," *Biological Psychology*, vol. 70, pp. 61–66, 2005.

[7] Y. Song, S. Dixon, M. T. Pearce, and A. R. Halpern, "Perceived and induced emotion responses to popular music: categorical and dimensional models," *Music Perception*, vol. 33, no. 4, pp. 472–492, 2016.

[8] M. M. Bradley and P. J. Lang, "Measuring emotion: The self-assessment manikin and the semantic differential," *Journal of Behavior Therapy and Experimental Psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.

[9] J. A. Russell, "Core affect and the psychological construction of emotion," *Psychological Review*, vol. 110, pp. 145–172, 2003.

[10] D. Sammler, M. Grigutsch, T. Fritz, and S. Koelsch, "Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music," *Psychophysiology*, vol. 44, pp. 293–304, 2007.

[11] T. Schäfer, P. Sedlmeier, C. Städtler, and D. Huron, "The psychological functions of music listening," *Frontiers in Psychology*, vol. 4, no. 511, pp. 1–33, 2013.

[12] V. N. Salimpoor, M. Benovoy, G. Longo, J. R. Cooperstock, and R. J. Zatorre, "The rewarding aspects of music listening are related to degree of emotional arousal," *PLoS ONE*, vol. 4, no. 10, pp. 1–14, 2009.

[13] F. S. Ribeiro, F. H. Santos, P. B. Albuquerque, and P. Oliveira-Silva, "Emotional induction through music: measuring cardiac and electrodermal responses of emotional states and their persistence," *Frontiers in Psychology*, vol. 10, Mar. 2019.

[14] L.-O. Lundqvist, F. Carlsson, P. Hilmersson, and P. N. Juslin, "Emotional responses to music: experience, expression, and physiology," *Psychology of Music*, vol. 37, no. 1, pp. 61–90, 2008.

[15] E. Mas-Herrero, R. J. Zatorre, A. Rodriguez-Fornells, and J. Marco-Pallarés, "Dissociation between musical and monetary reward responses in specific musical anhedonia," *Current Biology*, vol. 24, no. 6, pp. 699–704, 2014.

[16] M. Sumpf, S. Jentschke, and S. Koelsch, "Effects of aesthetic chills on a cardiac signature of emotionality," *PLoS ONE*, vol. 10, no. 6, pp. 1–16, 2015.

[17] J. T. Cacioppo, G. G. Berntson, J. T. Larsen, K. M. Poehlmann, and T. A. Ito, "The psychophysiology of emotion," *The Handbook of Emotion*, M. Lewis and J. M. Haviland-Jones, Eds. New York: Guilford Press, 2000, pp. 173–191.

[18] S. Khalfa, I. Peretz, J.-P. Blondin, and R. Manon, "Event-related skin conductance responses to musical emotions in humans," *Neuroscience Letters*, vol. 328, no. 2, pp. 145–149, 2002.

[19] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm, "Looking at pictures: Affective, facial, visceral, and behavioral reactions," *Psychophysiology*, vol. 30, no. 3, pp. 261–273, 1993.

[20] N. S. Rickard, "Intense emotional responses to music: A test of the physiological arousal hypothesis," *Psychology of Music*, vol. 32, no. 4, pp. 371–388, 2004.

[21] A. Gabrielsson and P. N. Juslin, "Emotional expression in music," *Handbook of affective sciences*, R. J. Davidson, K. R. Scherer, and H. H. Goldsmith, Eds. Oxford, UK: Oxford University Press, 2003, pp. 503–534.

[22] L. Bernardi, C. Porta, and P. Sleight, "Cardiovascular, cerebrovascular, and respiratory changes induced by different types of music in musicians and non-musicians: the importance of silence," *Heart*, vol. 92, no. 4, pp. 445–452, 2006, pMID: 16199412; PMCID: PMC1860846.

[23] S. Saguna and K. Deepika, "The effects of music on pulse rate and blood pressure in healthy young adults," *International Journal of Research in Medical Sciences*, vol. 5, no. 12, pp. 5268–5272, 2017.

[24] K. B. Scherer and M. R. Zentner, "Emotional effects of music: Production rules," *Music and Emotion: Theory and Research*, P. N. Juslin and J. A. Sloboda, Eds. Oxford, UK: Oxford University Press, 2001, pp. 361–392.

[25] N. J. Dibben, "The role of peripheral feedback in emotional experience with music," *Music Perception*, vol. 22, no. 1, pp. 79–115, 2004.

[26] L. Bernardi, C. Porta, and P. Sleight, "Dynamic interactions between musical, cardiovascular, and cerebral rhythms in humans," *Circulation*, vol. 119, no. 25, pp. 3171–3180, 2009.

[27] S. H. Fairclough, M. van der Zwaag, E. Spiridon, and J. Westerink, "Effects of mood induction via music on cardiovascular measures of negative emotion during simulated driving," *Physiology & Behavior*, vol. 129, pp. 173–180, 2014.

[28] J. K. Vuoskoski and T. Eerola, "Measuring music-induced emotion: A comparison of emotion models, personality biases, and intensity of experiences," *Musicae Scientiae*, vol. 15, no. 2, pp. 159–173, 2011.

[29] D. Makowski, T. Pham, Z. J. Lau, J. C. Brammer, F. Lespinasse, H. Pham, C. Schölzel, and S. H. A. Chen, "NeuroKit2: A python toolbox for neurophysiological signal processing," *Behavior Research Methods*, vol. 53, no. 4, pp. 1689–1696, 2021.

[30] V. K. M. Cheung, T. Harada, S. Sakamoto, and S. Furuya, "Spectral acoustic contributions to musical pleasure are dynamically shaped by autonomic neural inputs," *bioRxiv*, 2025, preprint. (available at: *https://doi.org/10.1101/2025.01.05.631396*).