RESEARCH ARTICLE

Measuring the Effects of Unexpected Deviations of Musical Patterns on Predictive Brain Functions

Alpana Durbha, Richard Yu

Lynbrook High School, 1280 Johnson Ave, San Jose, CA 95129; alpana.durbha@gmail.com

ABSTRACT: Music, composed of recurring patterns of rhythm, harmony, and melody, provides a unique framework to study the brain's predictive functions. Predictive-coding theories propose that the brain continuously anticipates upcoming sensory events and generates prediction-error responses when expectations aren't met. In music, prediction errors can arise from rhythmic, harmonic, or melodic deviations, each of which may engage distinct neural mechanisms. This study evaluated two hypotheses using a low-cost, consumer-grade EEG system (MUSE 2® Headband): (1) that the experimental setup can reliably detect distinguishable brainwave responses associated with prediction-errors arising from rhythmic, harmonic, and melodic deviations; and (2) that these responses exhibit spatially distributed and hierarchical patterns across EEG sensor–frequency band combinations. The primary performance metric was detection rate, defined as the proportion of trials in which brainwave signals exhibited a statistically significant effect of prediction-error versus control stimuli (repeated-measures ANOVA, $p < 0.05$), with values > 70% considered sufficiently high for a low-cost alternative. Results demonstrated consistently strong detection rates of prediction-error for all experiments, with harmonic deviations producing the largest effects (78%) relative to rhythmic deviations (70%). These findings indicate that this experimental setup, with consumer-grade EEG hardware, offers an accessible platform for studying the neural mechanisms of predictive function.

KEYWORDS: Medical and Health Sciences, Neuroscience, Brain, Predictive Functions, Electroencephalogram (EEG).

Introduction

Music is composed with recurring patterns of rhythm, harmony, and melody, and prior research shows that these regularities lead the brain to form predictions of what comes next, based on the pattern seen so far in the songs/musical compositions. Specifically, the Predictive Coding of Music (PCM) framework proposes that the brain does not passively perceive music, but actively anticipates it.[1] When the expected musical pattern is disturbed by a syncopated or an aberrant note, the brain generates a "prediction error", which is resolved through specific neural mechanisms involving the auditory and motor cortices.[2] As the brain continuously updates its internal model by comparing expected and actual input, this transition into a predictive-error state causes measurable changes in brain wave activity across the delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (30–70 Hz) frequency bands which can be detected by Electroencephalography (EEG).[2,3]

MUSE 2® Headband is a consumer-grade EEG measuring device. It has four EEG recording sensors: AF7, AF8, located in the frontal region of the headband, and TP9, TP10, located in the temporoparietal region of the headband. The brain's prediction error response is spatially distributed across different brain regions, processing different aspects of the error response.[4] According to PCM theory, lower-level predictions, such as rhythm, depend on immediate sensory input and short-range musical patterns. High-level predictions, such as harmony, depend on syntactic relationships and long-range musical patterns.[4] The spatial and hierarchical aspects are important in understanding the neural mechanisms involved in prediction-error responses.

While much of the existing literature, particularly the foundational work by Vuust and Witek,[5] focuses on rhythmic syncopation as the primary trigger of prediction-error responses, far less research has examined the impact of harmonic or melodic deviations on brain activity. In addition, most studies in this field rely on clinical-grade EEG systems, which can limit accessibility and hinder widespread replication. The objective of the present work is threefold: first, to evaluate whether low-cost, consumer-grade EEG technology (MUSE 2® Headband) can reliably capture brainwave signatures of predictive processing; second, to investigate whether different types of prediction errors—such as temporal deviations (rhythm) and tonal deviations (harmony)—produce distinct effects on the brain's predictive-processing mechanisms; and third, to assess whether this setup can detect signatures of the spatially distributed and hierarchical organization proposed by predictive-coding models.

This approach of understanding the brain's predictive functions can offer exciting potential for understanding experimentally the neural mechanisms underlying prediction and its implications for developing therapies for neurological and emotional disorders, such as functional neurological disorders and neuropsychiatric disorders, which can be understood as prediction-error processing abnormalities.[6,7]

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Methods

Audio files preparation and Trial Design:

The GarageBand® application was used to create and record separate audio files of melody, harmony, and rhythm of a section of a popular, recognizable theme song (based on the Star Wars theme song). Two variations of each of melody, harmony, and rhythm were created: a control file, which had all the original notes of the theme song, and a file with syncopated aberrations (pattern deviations in the notes of the theme song).

The audio files were arranged following a standard auditory oddball paradigm, a well-established experimental design used to elicit prediction error responses.[6] In this framework, a frequent standard stimulus (the control file) establishes a predictive model, which is subsequently disturbed by a rare deviant stimulus (the syncopated file).

The Audacity® application was used to combine the two types of files (control file + file with deviation) into independent trials of melody, harmony, and rhythm. A trial consists of 7 segments: 1 quiet segment with no music for 10 secs, followed by five repetitions of the control file (either melody, harmony, or rhythm), and ending with one segment of the file containing the syncopated aberration. Six of the same trials (six repetitions) were combined into one independent audio file each for melody, harmony, and rhythm.

Statistical Analysis (ANOVA):

The repeated-measures ANOVA was used as the core statistical tool to determine whether the brain shows a prediction-error response when a musical pattern unexpectedly deviates. Each trial contains:

• Control segments (Segments 1–6) → expected musical pattern

• Deviation segment (Segment 7) → unexpected syncopation

For each participant, sensor, and frequency band, Power Spectral Density (PSD) is obtained for:

• Baseline (control)

• Prediction-error (deviation)

The repeated-measures ANOVA tests whether the brain's response during the deviation segment is statistically distinguishable from the response during the control segments.

The repeated-measures ANOVA was appropriate due to the following reasons:

• The same participant experiences both control and deviation conditions.

• PSD values are measured repeatedly across multiple trials, multiple sensors, and multiple frequency bands.

• It accounts for within-subject variability, which is crucial given the small sample size and EEG noise.

Data collection:

The MUSE 2® headband was used to record the brain wave activity as the participants listened sequentially to the three different audio files: rhythm, melody, and harmony. To measure brainwaves, the sampling rate (data collection) must be at least twice the signal's bandwidth (per Nyquist's theorem). Therefore, to enable detection of higher frequency Gamma waves (30-100 Hz), the recording interval in the Mind Monitor Application was set at 256 data points/sec.

An initial cohort of 15 volunteers participated in the study. Because frontal EEG sensors are susceptible to contamination from eye blinks and eye movements, the experimental protocol was modified to reduce ocular artifacts. For the final dataset, participants were instructed to keep their eyes closed throughout the recording session. Data from six participants who completed the experiment under this artifact-minimized condition were included in the analyses reported in this study.

For each audio file, data were collected by four sensors: AF7, AF8, located in the frontal region of the headband, and TP9, TP10, located in the temporoparietal region of the headband. The brainwave activity data recorded from the four sensors (AF7, AF8, TP9, and TP10) of the MUSE 2® headband were converted into Power Spectral Density (PSD) values for the five brain wave frequencies (delta, theta, alpha, beta, and gamma) using the Mind Monitor application (Figure 1). PSD data from all audio files was downloaded into Microsoft Excel for further processing. Prediction errors data per participant for the rhythm, harmony, and melody sections are included in the Appendix.

Figure 1: Mind monitor output showing per-FFT-window averaged Power Spectral Density (PSD) values for the Delta, Theta, Alpha, Beta, and Gamma bands while a participant listened to an audio stimulus, recorded using MUSE 2® Headband.[10,11]

Results

Data Quality and Sample Selection:

Preliminary repeated-measures ANOVA analyses conducted on data from the initial cohort indicated high variability across trials, with fewer than half of the trials exhibiting statistically significant prediction-error effects. Visual inspection and signal characteristics suggested that ocular artifacts, particularly affecting the frontal sensors (AF7 and AF8), contributed substantially to this variability.

Following the implementation of an eyes-closed recording protocol, data quality improved markedly. In the artifact-minimized dataset, approximately 70% of trials demonstrated statistically significant differences between control and deviation segments (repeated-measures ANOVA, $p < 0.05$). Accordingly, all subsequent analyses presented in this study are based on data from six participants who completed the experiment under these controlled conditions.

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Interpretation of Radial Charts (Figures 2, 3, and 4):

The radial charts in Figures 2, 3, and 4 visualize how each sensor-frequency band combination showed a statistically significant prediction-error response during the rhythmic, harmonic, and melodic experiments. Data across participants is represented in these figures. Each axis in the radial chart represents a specific sensor / brain-wave combination. Distance from the center represents the percentage of ANOVA tests that reached statistical significance for that condition.

Hierarchical Sensitivity: Dominance of Harmonic Prediction Errors:

The most significant finding of this study is the stronger neural response to harmonic deviations. It is important to clarify that this dominance is observed specifically within the limits of the set of observable events in our experimental framework. As illustrated in Figures 2, 3, and 4, under the defined conditions, the detection rates (responses) observed of the brain's predictive error function to harmonic deviations were consistently statistically significant in more trials (77.8% of the analyzed conditions) compared to rhythmic (70.8 %) or melodic (75.0 %) patterns. This suggests that while the brain creates strong models for timing (rhythm), it may be more acutely sensitive to violations of tonal expectation (harmony), suggesting a correlation with the hierarchical framework of PCM. In the context of a "popular, recognizable theme song," a wrong note (harmonic error) appears to generate a stronger error response-related activity in the predictive system than a mistimed beat.

Spatial Sensitivity: Cognitive Prediction vs. Basic Sensory Reaction:

The sensor data shown in the Radar Charts (Figures 2, 3, and 4) enables a better understanding of the kind of prediction error the brain is producing. A major question in this area of research is whether the brain is simply reacting to the unexpected sound with a basic sensory reaction (a simple reflex and not a deliberate cognitive evaluation of the event) or whether it is generating a "cognitive prediction error" (a sign that the brain's expectations were violated).[12] The results from the Harmony Experiments (Figure 3) support the idea that the response is more than just a simple reflex. If the response were only a basic sensory reaction, we would expect the strongest activity to appear in the temporal sensors (TP9/TP10) only. The accompanying strong response in AF8 as well suggests that the brain is actively noticing that the discordant note does not match the expected musical pattern—a sign of a cognitive prediction error. This confirms the experimental setup's ability to map the spatially distributed nature of cognitive prediction error processing in correlation with the spatial framework of PCM.

Limitations:

Although this study shows that low-cost EEG devices can be used to detect predictive-coding responses in the brain, the limitations listed below should be considered when interpreting the results.

EEG recordings—especially frontal sensors like AF7 and AF8—are easily affected by eye movements and blinks. These "ocular artifacts" create strong electrical signals that can look similar to real brain activity, particularly in lower-frequency bands such as Delta and Theta. The initial study design included 15 participants, and upon data processing, errors potentially due to "ocular artifacts" were identified. Hence, the study design was modified, and experiments were repeated with six participants who kept their eyes closed during the entire duration of the experiment to eliminate errors due to blinking. Data from the six participants are reported in this article. Future studies may involve a larger group to confirm that these patterns hold more broadly.

The MUSE 2® headband uses only four dry electrodes (AF7, AF8, TP9, TP10), which provide a lower spatial resolution than medical-grade EEG systems with many more sensors. Hence, this study can only identify broad regions of activity (such as "frontal" or "temporoparietal") rather than pinpointing the exact brain areas involved. Future research could improve these limitations by including more participants, using stronger artifact-removal techniques, and analyzing raw EEG signals to compare event-related potentials (ERPs) with spectral-power results.

Conclusion on Variability:

The results also revealed meaningful variability across participants, suggesting that the strength of the "predictive model" is subjective and likely influenced by individual differences in musical experience. However, the overarching trend—Harmonic dominance and Frontal-Lobe engagement—validates that this accessible experimental setup can reliably detect complex predictive brain functions.

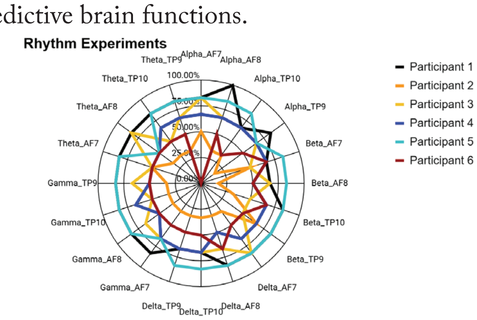

Figure 2: For rhythm experiments: Percentage of $p < 0.05$ for each participant from ANOVA analysis, for each sensor/brain wave combination. A high detection rate (70.8 % of all analyzed conditions) was observed for participants listening to a rhythmic pattern.

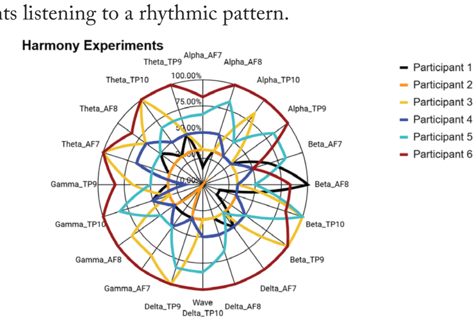

Figure 3: For harmony experiments: Percentage of $p < 0.05$ for each participant from ANOVA analysis, for each sensor/brain wave combination. The highest detection rate (77.8 % of all analyzed conditions) was observed for participants listening to a harmonic pattern, suggesting a correlation with the hierarchical framework of PCM.

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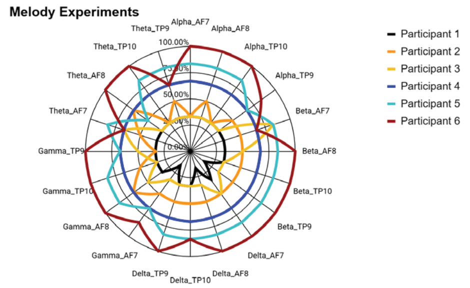

Figure 4: For melody experiments: Percentage of $p < 0.05$ for each participant from ANOVA analysis, for each sensor/brain wave combination. A high detection rate (75.0% of all analyzed conditions) was observed for participants listening to a melodic pattern.

Conclusion

This study demonstrated that low-cost EEG technology (such as available through MUSE 2® headband) can reliably detect and quantify the brain's predictive coding mechanisms in response to musical stimuli. The experimental setup was able to replicate complex "oddball paradigm" results typically observed in clinical environments.

Significant error responses were observed with all the prediction-error components of a musical sequence—rhythmic, harmonic, and melodic deviations. The primary finding of this research is the stronger neural response to harmonic deviations within the studied framework, suggesting a correlation with the hierarchical model of PCM. Existing literature often emphasizes rhythmic syncopation as the primary cause of prediction error, whilst data from this research suggests that deviations in harmonic patterns elicit a statistically significantly high detection rate in 77.8 % of analyzed conditions, which is higher than that observed for rhythmic or melodic patterns. Thus, it can be inferred that a wrong note (harmonic error) appears to generate a stronger signal to the predictive system than a mistimed beat (rhythm).

The strong engagement of the frontal lobe sensors (AF7/AF8), distinct from the temporal lobe activity, indicates that the frontal cortex is actively evaluating the stimulus. This confirms the experimental setup's ability to map the spatially distributed nature of cognitive prediction error processing: the brain is not just "hearing" a strange sound; it is actively judging that the sound does not belong in its internal model of the pattern. This aligns with the PCM, suggesting that the brain actively compares incoming sensory data against an anticipated pattern of musical notes.

Overall, these results validate that low-cost EEG technology, when paired with rigorous experimental design, can be a powerful tool for studying the brain's predictive function model. The experiment also revealed meaningful variability across participants, brainwave types, and sensor locations, suggesting the involvement of diverse neural mechanisms. Recent studies examining direct measures of brain energy and metabolism may further complement brainwave-based approaches, and integrating such methods could enhance the quality and interpretability of future predictive-processing measurements.[10]

Data Availability

The raw EEG datasets generated during the current study and the code used for the statistical analysis are available in the GitHub repository: https://github.com/aldurado/Music-2Brain.

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Authors

Alpana Durbha is a junior at Lynbrook High School in California. She has been deeply interested in Neuroscience and Neurotechnology and has furthered this interest by attending summer programs, serving in the school's Neuroscience/Psychology clubs, and conducting research in this field as a student of ASDRP (Aspiring Scholars Direct Research Program). Passionate about music, she has performed on the violin at several concerts in California and won the 2nd place at an international competition for Indian classical music. Her community engagements have included volunteering to care for seniors with neurological conditions and participating as a violinist in a fundraiser for an international non-profit organization.

Richard Yu is a sophomore at Lynbrook High School in California with strong academic interests in engineering and applied sciences. He serves as an officer on his school's robotics team, where he contributes to engineering design, problem-solving, and technical leadership. Outside the classroom, Richard complements his academic pursuits with leadership and service as a swim instructor, lifeguard, and Life Scout.

Appendix

Table 1: Prediction errors per participant for Rhythm.

Wave	Rhythm					
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5	Participant 6
Alpha_AF7	83.33%	50.00%	83.33%	66.67%	83.33%	0.00%
Alpha_AF8	100%	33.33%	66.67%	66.67%	83.33%	50.00%
Alpha_TP10	66.67%	33.33%	66.67%	66.67%	83.33%	33.33%
Alpha_TP9	83.33%	16.67%	66.67%	66.67%	66.67%	50.00%
Beta_AF7	66.67%	50.00%	50.00%	66.67%	83.33%	66.67%
Beta_AF8	66.67%	16.67%	66.67%	50.00%	83.33%	50.00%
Beta_TP10	83.33%	33.33%	50.00%	66.67%	83.33%	66.67%
Beta_TP9	83.33%	66.67%	50.00%	66.67%	83.33%	50.00%
Delta_AF7	83.33%	33.33%	83.33%	66.67%	83.33%	50.00%
Delta_AF8	83.33%	33.33%	66.67%	50.00%	83.33%	66.67%
Delta_TP10	66.67%	33.33%	66.67%	66.67%	83.33%	50.00%
Delta_TP9	66.67%	33.33%	66.67%	66.67%	83.33%	50.00%
Gamma_AF7	83.33%	33.33%	66.67%	66.67%	66.67%	50.00%
Gamma_AF8	83.33%	33.33%	66.67%	50.00%	83.33%	50.00%
Gamma_TP10	83.33%	33.33%	50.00%	66.67%	83.33%	50.00%
Gamma_TP9	83.33%	33.33%	66.67%	50.00%	83.33%	50.00%
Theta_AF7	83.33%	50.00%	50.00%	50.00%	83.33%	50.00%
Theta_AF8	83.33%	33.33%	83.33%	50.00%	50.00%	50.00%
Theta_TP10	83.33%	33.33%	50.00%	66.67%	83.33%	50.00%
Theta_TP9	83.33%	33.33%	66.67%	66.67%	83.33%	50.00%

Table 2: Prediction errors per participant for harmony.

Wave	Harmony					
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5	Participant
Alpha_AF7	16.67%	33.33%	33.33%	50.00%	66.67%	83.33%
Alpha_AF8	33.33%	33.33%	33.33%	50.00%	83.33%	100.00%
Alpha_TP10	33.33%	33.33%	83.33%	33.33%	50.00%	100.00%
Alpha_TP9	33.33%	33.33%	33.33%	33.33%	83.33%	100.00%
Beta_AF7	66.67%	33.33%	33.33%	50.00%	83.33%	50.00%
Beta_AF8	100.00%	33.33%	33.33%	33.33%	50.00%	83.33%
Beta_TP10	16.67%	33.33%	100.00%	33.33%	100.00%	83.33%
Beta_TP9	16.67%	33.33%	100.00%	50.00%	50.00%	100.00%
Delta_AF7	50.00%	33.33%	33.33%	50.00%	33.33%	100.00%
Delta_AF8	33.33%	33.33%	33.33%	50.00%	66.67%	100.00%
Delta_TP10	33.33%	33.33%	33.33%	50.00%	83.33%	100.00%
Delta_TP9	33.33%	33.33%	100.00%	33.33%	83.33%	100.00%
Gamma_AF7	33.33%	0.00%	83.33%	50.00%	50.00%	100.00%
Gamma_AF8	33.33%	33.33%	83.33%	33.33%	50.00%	100.00%
Gamma_TP10	50.00%	33.33%	33.33%	50.00%	83.33%	100.00%
Gamma_TP9	33.33%	33.33%	66.67%	16.67%	50.00%	83.33%
Theta_AF7	33.33%	33.33%	100.00%	66.67%	50.00%	100.00%
Theta_AF8	50.00%	33.33%	66.67%	66.67%	50.00%	83.33%
Theta_TP10	33.33%	33.33%	100.00%	50.00%	66.67%	100.00%
Theta_TP9	50.00%	33.33%	50.00%	50.00%	66.67%	100.00%

Table 3: Prediction errors per participant for Melody.

Wave	Melody					
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5	Participant 6
Alpha_AF7	33.33%	33.33%	33.33%	66.67%	83.33%	100.00%
Alpha_AF8	33.33%	50.00%	33.33%	66.67%	83.33%	100.00%
Alpha_TP10	33.33%	33.33%	33.33%	66.67%	83.33%	100.00%
Alpha_TP9	33.33%	50.00%	33.33%	66.67%	66.67%	83.33%
Beta_AF7	33.33%	50.00%	83.33%	66.67%	83.33%	66.67%
Beta_AF8	33.33%	50.00%	50.00%	66.67%	83.33%	100.00%
Beta_TP10	33.33%	50.00%	33.33%	66.67%	83.33%	100.00%
Beta_TP9	16.67%	50.00%	33.33%	66.67%	83.33%	100.00%
Delta_AF7	33.33%	50.00%	50.00%	66.67%	83.33%	100.00%
Delta_AF8	16.67%	50.00%	33.33%	66.67%	83.33%	100.00%
Delta_TP10	33.33%	50.00%	33.33%	66.67%	83.33%	83.33%
Delta_TP9	33.33%	50.00%	33.33%	66.67%	83.33%	100.00%
Gamma_AF7	16.67%	50.00%	33.33%	66.67%	66.67%	83.33%
Gamma_AF8	33.33%	66.67%	50.00%	66.67%	83.33%	100.00%
Gamma_TP10	33.33%	50.00%	33.33%	66.67%	83.33%	100.00%
Gamma_TP9	33.33%	33.33%	50.00%	66.67%	66.67%	100.00%
Theta_AF7	33.33%	50.00%	66.67%	66.67%	83.33%	66.67%
Theta_AF8	33.33%	66.67%	33.33%	66.67%	50.00%	100.00%
Theta_TP10	33.33%	33.33%	33.33%	66.67%	83.33%	100.00%
Theta_TP9	33.33%	50.00%	33.33%	66.67%	83.33%	66.67%

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