Electroencephalographic Engagement Indices for the Discrimination of Induced Emotions During Music Listening

Giuseppe Legista
Università Politecnica delle Marche
(UNIVPM)
Ancona, Italy
S1114384@studenti.univpm.it

Mauro Silveri
Università Politecnica delle Marche
(UNIVPM)
Ancona, Italy
S1114536@studenti.univpm.it

Davide Pitucci
Università Politecnica delle Marche
(UNIVPM)
Ancona, Italy
S1114470@studenti.univpm.it

Christian Di Salvo
Univeristà Politecnica delle Marche
(UNIVPM)
Ancona, Italy
S1114425@studenti.univpm.it

Abstract—This study explores the use of EEG-derived engagement indices to investigate the emotional impact of music listening. The primary objective is to identify the most effective indices for distinguishing between resting state and music listening, between positive and negative emotions elicited by music, and between various pairs of music-induced emotions. EEG data were analyzed using the EEGLAB toolbox, incorporating independent component analysis as well as time and frequency domain analyses. A total of 37 engagement indices were computed, and the Wilcoxon test was employed to determine those with the highest discriminative power. Among these, the indexes I1, I4, I5, I7, I11, I12, I19, I22, I24, I25, I26, I27, I28, I39, I35, I36 proved to be the most effective in differentiating between resting state and music listening state. Whereas the most significant EEG channels were Fp1, Fp2, F4, F8, T3, C3, Cz, Pz, T6, O1, and O2.

Additionally, several indexes showed the ability to discriminate among specific emotions induced by music, particularly in the frontal, parietal, and occipital regions. These findings contribute to a deeper understanding of how music influences emotional processing and highlight which brain areas are most involved in response to specific emotional states.

Keywords—ICA, EEG, engagement index, emotional response, emotional engagement, music listening, EEGLab

I. Introduction

Emotions involve physiological, psychological and behavioral responses triggered by external stimuli. Through the joint use of facial expression analysis and physiological signals acquisition such as electroencephalography (EEG) and electrocardiography (ECG) it is possible to recognize and categorize emotions. This is important in many fields, especially in mental health studies. Among other techniques, EEG is particularly effective because it provides objective real-time data that is not influenced by conscious control. Recent studies show that music plays a central role in daily life, helping people connect socially and express complex emotions. In some cases, music is used in treating mental disorders because it acts as a powerful emotional stimulus and can trigger a wide range of responses. Through years of studies datasets, EEG and relative physiological data while subjects listened to affective music have been collected showing a clear link between these signals and self-reported emotional responses. Emotion recognition could be helpful in the diagnosis of depression, schizophrenia and other mental diseases [1]. A key concept for these kinds of studies is mental engagement, defined as focused attention and active participation during a task, which goes beyond basic cognitive processing. EEG is the most suitable tool to measure this, as it detects electrical activity resulting from synchronized neural firing. EEG frequency bands are grouped into six categories:

1. Delta **δ** (0.5–4 Hz)
2. Theta **θ** (4–8 Hz)
3. Alpha **α** (8–12 Hz)
4. Sensorimotor rhythm - **SMR** (12–15 Hz) [2]
5. Beta **β** (15–35 Hz)
6. Gamma **γ** (35–70 Hz)

The concepts of mental engagement and relative brain activation (with its own frequency bands) can be merged obtaining engagement indexes. These were introduced to measure mental involvement during tasks [3] and have since been extended in various ways. They are calculated as ratios between the spectral powers of these bands and can be divided into basic and derived forms. Commonly used ratios include β/α, $\beta/(\alpha + \theta)$, β/θ, and θ/α. Indices can also be calculated as the difference between hemispheres to assess asymmetry in brain activity. Some derived indices are obtained through mathematical transformations or specific analysis on selected bands. Recently, large EEG datasets on music and emotion have been made available, allowing for deeper analysis across multiple brainwave types. These studies improve understanding of how mental engagement and emotional responses interact, reinforcing the value of EEG in psychological research. In this study the aim is to identify which engagement ratio indices are most effective in characterizing the emotional effects of music listening. Furthermore, the following analysis focuses on three main parts:

- Distinguishing music listening state from resting state
- Identifying and comparing different emotions
- Comparing pleasant and unpleasant emotions

II. Materials and methods

The EEG data analyzed in this study are publicly available on OpenNeuro under the title: "An EEG dataset recorded during affective music listening." (with corresponding dataset DOI: 10.18112/openneuro.ds002721.v1.0.2) [4]. The dataset includes recordings from 31 healthy adult participants, each identified under the format "*sub-s_number*", denoting a randomly assigned participant number ranging from 1 to 31. Each subject has undergone six EEG recording sessions (runs), each one of them available. The first (run1) and sixth (run6) runs correspond to resting-state conditions, where subjects were instructed to remain seated and motionless for 300 seconds. The remaining four runs (run2, run3, run4, run5) consist of music listening sessions, each containing 10 musical excerpts, each with a duration of 12 seconds. After listening to each excerpt, participants responded to eight questions assessing the emotional response elicited by the music. The emotional dimensions evaluated were pleasantness, energy, tension, anger, fear, happiness, sadness and tenderness. Responses were given on a 9-point Likert scale, indicating the perceived intensity of each emotion. The dataset comprises raw EEG recordings from both music listening and resting-state conditions, stored in ".edf" format, along with corresponding metadata in ".json" format. Additional information regarding EEG channel configurations is provided in ".tsv" files. Participants' self-reported emotional responses are also available in ".tsv" files, accompanied by associated metadata in ".json" format. The participants were healthy adults, being between 18 and 66 years old. EEG data were acquired using a BrainAmp EEG amplifier system (Brain Products, Germany). Recordings were obtained from 19 scalp electrodes positioned according to the international 10–20 system (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, PZ, P4, T6, O1, and O2). Electrode FCz was used as the reference, while AFz served as the ground electrode [5]. In accordance with updated nomenclature, four electrode labels were renamed: T3 as T7, T4 as T8, T5 as P7, and T6 as P8. The EEG signals were sampled at a rate of 1000 Hz. In this study, data from subjects 12 to 21 were analyzed, with a specific focus on run2 for the music listening condition and run1 for the resting-state condition. The preprocessing and analysis of raw EEG data were carried out using the EEGLAB toolbox in MATLAB. The procedure began with the import of the raw EEG file (e.g., sub-15_task-run1_eeg.edf), followed by the corresponding events file (sub-15_task-run1_events.tsv). This events file contains three columns—onset, duration, and trial type—which encode the temporal information of each stimulus and participant response, including music onset and offset, the questions presented, and the corresponding answers, all time-stamped in seconds. Channel location data were imported by generating a channel structure containing only the electrode labels, with the previously mentioned renaming of four electrodes from the 10–20 system (Figure II-1).

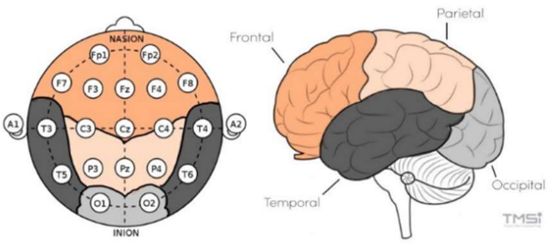

Figure II-1 – the 10-20 system

Using MATLAB, the EEG signals were resampled to 500 Hz and filtered using a third-order Butterworth bandpass filter with cutoff frequencies set at 0.5 Hz and 80 Hz. To eliminate power line noise at 50 Hz, the Cleanline plugin in EEGLAB was applied three times (in electrophysiology, band-stop filters are used to suppress line at 50/60 Hz depending on the country or cathode ray tube noise [6]). The EEG signals were then re-referenced using the average reference technique. Independent Component Analysis (ICA) was subsequently performed to identify and isolate artifacts. The ICLabel plugin was used to estimate the probability of each component belonging to one of six categories: Brain, Muscle, Eye, Heart, Line Noise, Channel Noise, or Other. Component classification followed a specific set of criteria: If the probability of a component being brain-related exceeded 50%, it was marked as "ACCEPT." If the brain component probability was below 50%, but all other categories were also below 50%, it was still marked as "ACCEPT." If the brain component probability was below 50% and at least one other category exceeded 50%, the component was marked as "REJECT." Doing so components not classified as brain-related were excluded, and the cleaned EEG signal was reconstructed. Twelve-second epochs were then extracted, corresponding to the duration of each music excerpt in run2, yielding 10 epochs per subject. From run1, a resting-state segment of equivalent duration was extracted from the final portion of the recording. Spectral power features and engagement indices were computed for each channel, index, subject, and epoch. The Wilcoxon signed-rank test was applied to compare the two conditions—music listening and resting state—with the aim of identifying the most discriminative engagement indices. Indices were considered significant if associated with a channel showing a p-value < 0.05. Subsequently, focusing exclusively on run2, pairs of opposing emotional states—specifically positive versus negative emotions—were analyzed to determine which engagement indices most effectively discriminated between these contrasting affective responses. Each musical excerpt was labeled with one of the eight primary emotions, enabling emotion-specific comparisons. An additional analysis step involved identifying the most statistically significant indices capable of distinguishing each perceived emotion from the others. The emotion pairings used are based on the *Circumplex Model of Affect*, proposed by James A. Russell in 1980 [7] (Figure II-2):

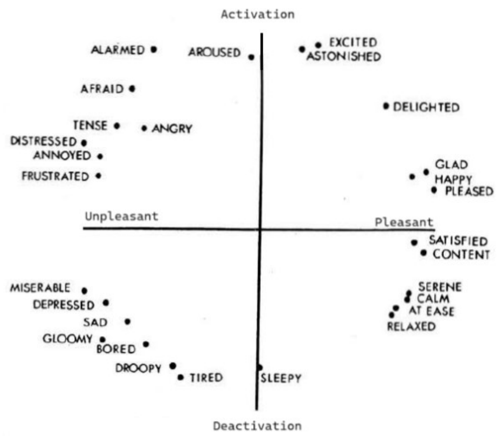

Figure II-2 – Circumplex Model of Affect

This model positions emotions within a two-dimensional space defined by **Valence** (ranging from negative emotional states (*Unpleasant*) to positive emotional states (*Pleasant*)) and **Arousal** (ranging from low levels of activation (*Deactivation*) to high levels of activation (*Activation*)). Emotions are then arranged around a circular structure to reflect their relationships according to these two dimensions. For instance, emotions such as afraid and angry share high arousal but differ in valence, while emotions like sad and happy differ in both valence and arousal. The following pairs, considered antipodean, were chosen:

- *Happy – Sad (■)*
- *Pleasant (Relaxed*) – Afraid (■)*
- *Tender (Serene*) – Angry (■)*
- *Energetic (Excited*) – Tense (Alarmed*) (■)*

(***-terms** refer to those reported in the circumplex model)

The final emotion pair, selected for the sake of completeness, was also defined with reference to the circumplex model. In this case, it was not possible to identify two emotions positioned at exact opposites, so the chosen pair was selected because both emotions are in opposite hemispheres (unpleasant vs. pleasant) at the same level of "Activation" (*Figure II-3*).

Figure II-3 - Pairing of emotions

III. Results.

A. Engagement Ratio Indices for the Comparison Between Music Listening and Resting-State Conditions

The selection of the most relevant EEG channels was based on a frequency threshold equal to the mean occurrence across all channels, calculated as 5.26%. The channels that exceeded this threshold are as follows:

- **FP1** (7.18%), **FP2** (5.52%), **F4** (5.80%), **F8** (6.35%), **T3** (6.63%), **C3** (7.73%), **CZ** (6.35%), **PZ** (6.35%), **O1** (6.35%), **T6** (5.52%), and **O2** (6.91%).

Similarly, for engagement indices, the threshold was defined as the mean frequency of 2.70%. The indices that surpassed this value and were therefore considered the most relevant are:

- **I1** (4.14%), **I4** (4.97%), **I5** (3.31%), **I7** (4.14%), **I11** (4.70%), **I12** (4.97%), **I19** (3.31%), **I20** (5.25%), **I22** (3.87%), **I24** (5.25%), **I25** (3.59%), **I26** (3.31%), **I27** (5.25%), **I28** (3.04%), **I30** (5.25%), **I35** (4.14%), and **I36** (3.59%).

B. Engagement Ratio Indices for the Comparison of Different Induced Emotions

The subsequent analysis aimed to identify engagement indices capable of discriminating between pairs of distinct emotions.
Tables 1 and 2 in the appendix A summarize the findings of the analysis extended to all possible pairs of different emotions to determine which engagement indices and EEG channels most effectively discriminated between them.
The following results summarize the most relevant indices along with most discriminative channels, expressed as percentages relative to the total number of significant cases:

- ***Afraid Vs Angry***: FP1 (100%), I28 (100%)
- ***Afraid Vs Energetic***: FP1 (15.24%), PZ (14.29%), FP2 (12.38%), I2 (9.52%), I9 (7.62%), I13 (7.62%), I14 (7.62%), I18 (7.62%), I23 (7.62%).
- ***Afraid Vs Pleasant***: FP1 (22.58%), F8 (19.35%), O1 (12.9%), O2 (12.9%), I1 (16.13%), I20 (22.58%), I30 (22.58%).
- ***Afraid Vs Sad:*** F8 (100%), I14 (50%), I23 (50%).
- ***Afraid Vs Tender***: FP1 (30.43%), P3 (34.78%), I1 (26.9%), I2 (13.04%), I27 (13.04%).
- ***Angry Vs Energetic***: FP1 (10.34%), O1 (10.34%), FP2 (20.69%), F8 (17.24%), I2 (10.34%), I23 (10.34%), I7 (17.24%), I35 (24.14%).
- ***Angry Vs Happy***: O1 (42.86%), I5 (28.57%), I13 (28.57%).
- ***Angry vs. Pleasant***: FP1 (37.5%), C3 (12.5%), CZ (20.83%), I7 (12.50%), I23 (12.50%), I28 (12.50%), I30 (12.50%).
- ***Angry vs. Sad***: C4 (100%), I7 (100%).
- ***Angry Vs Tender***: FP1 (15.69%), FP2 (15.69%), F8 (13.73%), I1 (9.80%) I2 (9.80%), I17 (19.61%).
- ***Energetic Vs Happy:*** FP2 (9.68%), F8 (9.68%), T4 (9.68%), O1 (9.68%), PZ (12.90%), I7 (16.13%), I35 (16.13%), I30 (12.9%), I2 (12.9%).
- ***Energetic Vs Pleasant:*** C3 (50%), I28 (33.33%).
- ***Energetic Vs Sad***: FP2 (10.49%), F7 (8.02%), PZ (8.02%), I1 (8.02%), I2 (8.02%), I23 (8.02%), I9 (8.64%).
- ***Energetic Vs Tender***: T3 (60%), I6 (13.33%), I36 (33.33%).
- ***Happy Vs Pleasant:*** FP1 (11.66%), F8 (11.66%), T3 (11.66%), C3 (23.53%), I19 (11.76%), I20 (11.76%), I28 (17.65%), I30 (29.41%).
- ***Happy Vs Sad***: F8 (100%), I14 (50%), I25 (50%).
- ***Happy Vs Tender***: F8 (11.76%), T3 (9.80%), C3 (7.84%), T4 (7.84%), I7 (13.73%), I11 (13.73%), I30 (29.41%).
- ***Pleasant Vs Sad***: FP1 (24.14%), F8 (34.48%), P3 (10.34%), I1 (20.69%), I24 (17.24%), I20 (13.79%), I2 (13.79%).
- ***Pleasant Vs Tender***: T3 (100%), I1 (33.33%), I24 (33.33%), I27 (33.33%).
- ***Sad Vs Tender***: FP1 (18.18%), FP2 (13.64%), F4 (9.09%), F8 (9.09%), PZ (9.09%), I1 (27.27%), I28 (22.73%), I36 (18.18%).

The missing elements are not reported in the previous list because null: ***Afraid Vs Happy, Afraid Vs Tense***, ***Angry Vs Tense***, ***Energetic Vs Tense***, ***Happy Vs Tense***, ***Pleasant Vs Tense***, ***Sad Vs Tense, Tender Vs Tense***. These findings highlight the variability and specificity of engagement indices and electrode locations in differentiating between pairs of induced emotional states.
To identify the neural markers that best differentiate emotional states, a classification was made by grouping emotions into two main categories:

- *Pleasant emotions*: Happy, Energetic, Pleasant, Tender
- *Unpleasant emotions*: Afraid, Angry, Sad, Tense

Therefore, by considering the findings earlier listed, the most effective channels and indexes to distinguish between **pleasant and unpleasant** emotions (based on their frequency relative to the total number of significant indices and channels), are:

- Channels: FP1, F8, FP2, PZ, O1, P3, T4, P4, O2
- Indexes: I1, I2, I7, I23, I28, I14, I20, I24, I30

IV. Discussion

The objective of this study is to evaluate whether engagement indices show significant differences between the resting-state and music listening conditions in the analyzed subjects. Additionally, the study aims to identify indices capable of distinguishing between positive and negative emotional states, as well as between specific pairs of induced emotions. Among the EEG channels identified as most significant, FP1 and FP2—located in the prefrontal region—stand out. These channels, along with F8 from the frontal area, are functionally associated with emotional regulation, cognitive processes such as planning and reasoning, problem-solving, and voluntary motor control. The T3 channel, positioned in the temporal region, encompasses the primary auditory cortex, which processes auditory input, and is closely linked to the hippocampus, playing a key role in learning and emotional processing. Channel C3 is primarily located over the sensorimotor cortex and is involved in motor and somatosensory functions. Finally, channels O1 and O2, situated in the occipital region, are responsible for visual processing and sensory integration, including the activity of the primary visual cortex and visual association areas. Regarding the engagement indices, several have been identified as particularly relevant for characterizing the emotional and cognitive states induced by music. Among them, the following indices are considered to have the greatest at describing the mental involvement in listening to music and discriminating against the type of emotion a certain music evokes in the subject:

- **I1** is the ratio between beta and alpha waves. Alpha activity is typically associated with relaxed, pleasant emotional states and beta activity is linked to active attention or anxiety, more frequent in unpleasant or stressful conditions. Reflects engagement and alertness with higher values indicate increased mental effort while lower values suggest pleasant or calm emotional states.

- **I20** is the ratio of alpha band power to gamma band power and evaluates alpha dominance during relaxation. Gamma activity is linked to cognitive load, working memory, attention, and emotional intensity (particularly arousal and sometimes anxiety). Hence, a lower I20 could correspond to unpleasant emotional experiences

- **I5** measures the ratio between theta and delta waves, with delta activity representing deep sleep or unconsciousness. I5 is indicative of whether music induces deep relaxation or drowsiness.

- **I4** reflects the ratio between theta and alpha waves. Theta activity is typically associated with creativity, relaxation, and dream-like states. This index is particularly useful for evaluating how specific types of music promote a relaxed yet conscious state.

- **I7** represents the ratio between the Sensory-Motor Rhythm (SMR) and beta waves. A higher value may indicate increased tension or stress, whereas a lower value may suggest deep relaxation.

- **I23** combines three frequency bands: alpha, beta, and theta. A higher value, due to high beta (engagement, alertness) or low theta (less emotional arousal / fatigue) reflects focused, mentally engaged, and possibly neutral/positive state. While a lower value due to high theta (drowsiness, emotional reactivity) or low beta suggests low engagement, emotional arousal, or fatigue/drowsiness.

Additionally, several indices were found to discriminate between two positive or two negative emotions:

- ***Happy vs. Pleasant*:** I19, I20, I28, I30
- ***Tender vs. Pleasant***: I1, I24, I27
- ***Tender vs. Energetic***: I6, I36
- ***Sad vs. Afraid***: I14, I23
- ***Angry vs. Afraid***: I28

The most frequent channels identified in the confrontation between emotions were the electrodes in the frontal, parietal and occipital region. Emotion pairs not listed above either did not yield statistically significant results or showed very low percentages of relevance relative to the entire set of indices and channels were therefore excluded from further analysis in this study.

V. Conclusions

The objective of the present study is to identify the most effective indices for distinguishing between the resting state and the music listening phase in the subject. Eleven channels were found to be significant (frequency above the average channel frequency threshold), and seventeen indexes were found to be recurring more than the average index frequency threshold, indicating that the indexes I1, I4, I5, I7, I11, I12, I19, I20, I22, I24, I25, I26, I27, I28, I39, I35, I36 may be the best indexes in discriminating if a subject is listening to music or not. In the discrimination of two opposing or even similar emotion states induced by music, the majority of engagement-related indices were identified as significant for specific channels, particularly those associated with the frontal, parietal and occipital lobes. The assessment of music-induced emotions presents a considerable challenge, as different modes of execution can evoke diverse sensations in the subject, owing to the varying styles of musical excerpts. Furthermore, the analysis is complicated by the fact that each musical clip may elicit distinct emotional responses in different individuals, influenced by factors such as personal life experiences, age, and musical preferences. An additional confounding variable is the self-assessment provided by subjects for each musical piece. Not all individuals can evaluate their emotional state efficiently and accurately based on their subjective experience. Moreover, electroencephalographic signals are inherently noisy and non-stationary, thus requiring extensive preprocessing before meaningful analysis can be conducted. The integration of physiological markers (e.g., heart rate variability, skin conductance) and behavioral indicators (e.g., facial expressions, body movements) alongside EEG data may contribute to a better and proper understanding of emotional responses. In conclusion, numerous variables influence the interpretation of EEG signals in this context, and the reliability of the identification of music-induced emotional states through EEG remains a complex and unresolved challenge in the field.

VI. Bibliography

[1] H. Liu, Y. Zhang, Y. Li e X. Kong, «Review on Emotion Recognition Based on Electroencephalography,» *National Libary of Medicine,* 1 October 2021.

[2] I. Marcantoni, R. Assogna, G. D. Borrello, M. D. Stefano, M. Morano, S. Romagnoli, C. Leoni, G. Bruschi, A. Sbrollini, M. Morettini e L. Burattini, «Ratio Indexes Based on Spectral Electroencephalographic Brainwaves for Assessment of Mental Involvement: A Systematic Review,» *Sensors (MDPI),* vol. EEG Signal Processing for Sensing Technologies in Biomedical Engineering Applications, 27 June 2023.

[3] A. T. Pope, E. H. Bogartb e D. S. Bartolomeb, «Biocybernetic system evaluates indices of operator engagement in automated task,» *Elsevier - Biological Psychology,* vol. 40, 1995.

[4] I. D. Nasuto, N. Nicolaou, D. Williams, F. Hwang, A. Kirke, E. Miranda e S. J., «An EEG dataset recorded during affective music listening,» *ResearchGate,* 2020.

[5] I. Daly, J. Hallowell, F. Hwang, A. Kirke, A. Malik, E. Roesch, J. Weaver, D. Williams, E. Miranda e S. J. Nasuto, «Changes in music tempo entrain movement related brain activity,» *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* 2014.

[6] A. Widmann, E. Schröger e B. Maess, «Digital filter design for electrophysiological data – a practical approach,» *Journal of Neuroscience Methods,* vol. 250, pp. 34-46, 2015.

[7] J. A. Russell, «A Circumplex Model of Affect,» *Journal of Personality and Social Psychology,* p. 1161–1178, 1980.

APPENDIX A

Table 1 Statistically significant channels in single pair emotion comparison

Main channels								
	Afraid	**Angry**	**Energetic**	**Happy**	**Pleasant**	**Sad**	**Tender**	**Tense**
Afraid	-							
Angry	FP1	-						
Energetic	FP1, FP2, F8, T4 P3, PZ, P4, O2	FP1, FP2, F8, O1	-					
Happy	/	O1	FP2, F4, F8, C3, T4, PZ, P4, O1, O2	-				
Pleasant	FP1, F8, O1, O2	FP1, C3, CZ	C3	FP1, F8, T3, C3, C4	-			
Sad	F8	C4	FP1, FP2, F7, FZ, F4, F8, C4, T4, P3, PZ, P4, O1, O2	F8	FP1, F8, P3	-		
Tender	FP1, P3	FP1, FP2, F8, T5, PZ	T3	FP1, FP2, F4, F8, T3, C3, CZ, T4, T5, PZ, P4, O1	T3	FP1, FP2, F4, F8, PZ	-	
Tense	/	/	/	/	/	/	/	-

Table 2 Statistically significant indexes in single pair emotion comparison

Main indexes								
	Afraid	**Angry**	**Energetic**	**Happy**	**Pleasant**	**Sad**	**Tender**	**Tense**
Afraid	-							
Angry	I28	-						
Energetic	I1, I2, I7, I9, I13, I14, I16, I18, I22, I23, I24, I28	I2, I7, I23, I35	-					
Happy	/	I5, I13	I2, I7, I30, I35	-				
Pleasant	I1, I20, I24, I27, I30	I2, I7, I12, I23, I28, I30	I28	I19, I20, I28, I30	-			
Sad	I14, I23	I7	I1, I2, I3, I6, I9, I13, I14, I21, I22, I23, I28	I14, I25	I1, I2, I20, I24	-		
Tender	I1, I2, I27	I1, I2, I7, I12, I20, I23, I30, I35	I6, I36	I7, I11, I19, I20, I30	I1, I24, I27	I1, I28, I36	-	
Tense	/	/	/	/	/	/	/	-