Polygon: Jurnal Ilmu Komputer dan Ilmu Pengetahuan Alam
Volume 3, Nomor 1, Tahun 2025
e-ISSN: 3046-5419; p-ISSN: 3032-6249, Hal. 103-115
DOI: https://doi.org/10.62383/polygon.v3i1.416
Available online at: https://journal.arimsi.or.id/index.php/Polygon

EEG Analysis of Emotional Responses to Classical Piano Music: Comparing Professional Pianists and Non-Musicians

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Abstract. This study aimed to explore the impact of classical piano music on emotional responses among professional pianists compared to non-professionals. The piano, known for its extensive pitch range and dynamic versatility, serves as a pivotal instrument in both classical and popular music. Previous research has examined how music influences individual's styles and behaviors. In our investigation, we analyzed electroencephalogram (EEG) signals to assess emotional responses in both groups, employing coherence measures. Listening tests were conducted to evaluate the effects of pitch and dynamics on emotional characteristics. Findings revealed that all ten emotional categories were significantly influenced by variations in pitch and dynamics. Specifically, emotions such as Happy, Romantic, Comic, Calm, Mysterious, and Shy generally increased with pitch, though a decline was observed at the highest pitches. Conversely, Heroic, Angry, and Sad emotions tended to decrease with rising pitch levels, while Scary emotions were pronounced at extreme low and high pitches. Regarding dynamics, emotions like Heroic, Comic, Angry, and Scary were more intense with loud notes, whereas Romantic, Calm, Mysterious, Shy, and Sad emotions were enhanced with softer notes. Notably, the emotion Happy showed no sensitivity to dynamic changes. These results provide valuable insights into the quantification of emotional characteristics associated with piano music.

Keywords: Classical Piano, EEG, Emotional Responses, Music.

1. INTRODUCTION

The proficiency required to play a musical instrument encompasses advanced auditory and motor processing skills. In this study, we examined the dynamic levels of sound—loud (forte), medium (mezzo), and soft (piano)—and their effects on ten emotional categories: Happy, Heroic, Romantic, Comic, Calm, Mysterious, Shy, Angry, Scary, and Sad. This research provides a foundational understanding of the emotional characteristics associated with piano music across various octaves and dynamics. The findings may offer valuable insights for recording engineers, composers, and pianists seeking to manipulate the emotional qualities of the instrument.

Our investigation focused on analyzing electroencephalogram (EEG) signals from pianists while they performed. Previous studies have explored EEG signals in musicians, including research by Schulze et al., which examined musicians during instrumental performances. Music has been shown to influence brain structure; for instance, Han et al. (2009) assessed gray matter density and white matter integrity in professional pianists

Received: Desember 26, 2024; Revised: Januari 14, 2025; Accepted: Januari 27, 2025; Published: Januari 30, 2025

compared to non-pianists using structural MRI and diffusion tensor imaging. Their findings indicated that professional pianists exhibited higher fractional anisotropy in the left sensorimotor cortex and right cerebellum, as well as enhanced white matter integrity relative to non-pianists.

In our study, we aimed to measure functional connectivity through EEG signals from two distinct groups: professional pianists and non-professionals. We specifically compared the effects of piano playing on emotional characteristics between these groups. Functional connectivity assesses the interrelationships between different brain regions, with coherence being one of its key measures. Notably, this approach has not been widely adopted in previous studies within this domain. While many investigations have utilized fMRI and MRI techniques, our research employed electroencephalography for data collection.

Upon recording EEG signals, we analyzed standard frequency bands and computed spectral coherence measures. Among various biomedical signal processing techniques—such as wavelet analysis, empirical mode decomposition, and bispectrum—we selected spectral coherence due to its demonstrated ability to produce robust features suitable for our analysis. This study contributes to a deeper understanding of the emotional dimensions of piano music and the underlying neural mechanisms involved in musical performance.

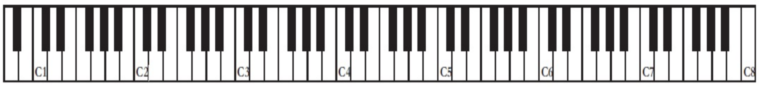

Figure 1. Selected pitches on the piano

Professional pianists were meticulously selected based on their advanced proficiency in piano performance, each possessing a minimum of five years of experience. All participants demonstrated the ability to skillfully play both the black and white keys simultaneously, as illustrated in Figure 1. They adeptly coordinated their hand movements while simultaneously engaging the pedals with their feet and interpreting musical scores. Furthermore, these pianists exhibited a remarkable capacity for memorizing notes and executing complex pieces with high proficiency.

The Piano

Extensive research has been conducted to explore emotional responses elicited by piano music. Several studies have investigated listener preferences regarding pitch, tempo, and timbre in solo piano excerpts. Findings indicate a preference for fast tempos and bright timbres, while no significant preference for pitch was noted. More broadly, research has differentiated the emotional responses to mechanical versus expressive piano performances, revealing distinct patterns of brain activation when listeners engage with different interpretations of the same musical piece. Although the timbre of the piano has been a subject of numerous studies, these investigations often overlook the emotional dimensions associated with timbre.

Pitch and Dynamics

A range of studies has examined the impact of varying pitch and dynamics on musical excerpts. Research focused on four MIDI musical excerpts revealed that while variations in dynamics significantly influenced listener ratings for both likability and emotional expressiveness, tempo did not have a notable effect. Additionally, an investigation into emotional responses to three-minute musical excerpts found that substantial variations in dynamics and pitch were linked to heightened ratings for the emotion of fear. Furthermore, studies comparing sine tones and MIDI synthesized piano melodies indicated that higher-pitched melodies were perceived as more submissive than their lower-pitched counterparts.

Despite the breadth of research addressing the effects of pitch, dynamics, and other musical elements such as tempo on listener preferences, there remains a gap in literature concerning how these factors influence the emotional characteristics of individual piano sounds. Previous studies have considered multiple dynamic levels (loud and medium-loud) while controlling for loudness to isolate the effects of timbre; however, all tones were standardized at E4 in those investigations.

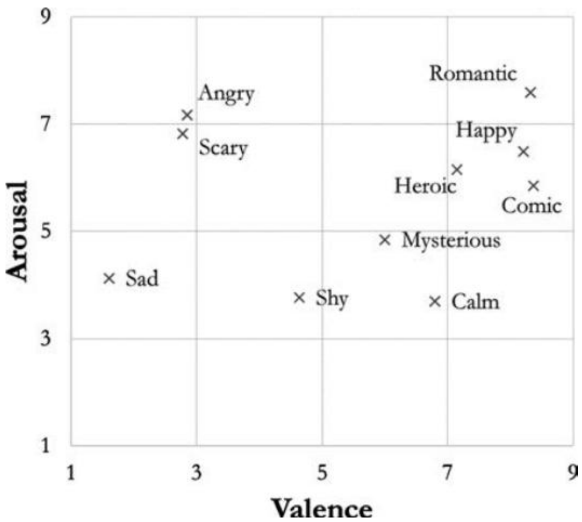

Figure 2. Distribution of the emotional characteristics in the dimensions of Valence and Arousal

The concepts of Valence and Arousal have been employed in various studies to categorize emotional responses. Our previous research demonstrated the statistical significance of these constructs when comparing sounds produced by single instruments. One notable advantage of utilizing a categorical emotional model, as opposed to a dimensional one, is the facilitation of quicker decision-making among listening test participants. Nonetheless, these emotional categories can still be represented within a dimensional framework. The ratings corresponding to this representation are illustrated in Figure 2, which employs the Valence–Arousal model. In this context, Valence reflects the positivity associated with an emotional category, while Arousal denotes the energy level of that category. Although emotions such as Scary and Angry exhibit similarities in terms of Valence and Arousal, they convey distinctly different meanings. Similarly, the emotions Romantic, Happy, Comic, and Heroic share comparable Valence and Arousal profiles but differ significantly in their interpretations.

Test Materials (Stimuli)

The stimuli utilized in the listening tests consisted of sounds generated by a grand piano, featuring various combinations of dynamics and pitch. All audio samples were sourced from the RWC Music Database and were performed by the same pianist on a Steinway grand piano (Piano #3, "Normal": 013PFNOF, 013PFNOM, 013PFNOP). Three distinct dynamic levels were employed: forte (the loudest), mezzo (moderate), and piano (the softest).

We meticulously evaluated all selected pitches and dynamics to ensure that the pianist's original dynamic expressions were consistent and appropriate across different pitches and dynamic levels; thus, no further adjustments to the amplitude of the samples were necessary. To mitigate any influence of pitch intervals beyond the octave on emotional characteristics, we exclusively selected C pitches from the piano (C1–C8), with C1 representing the lowest pitch and C8 the highest (as depicted in Figure 1). All sounds were recorded at a sampling rate of 44,100 Hz with 16-bit resolution and were subsequently played back using a D/A converter at 24-bit resolution while maintaining the original sampling rate. Any silence preceding the onset of each sound was eliminated, and sound durations were truncated to 1.0 second with a 30 ms linear fade-out applied before each sound's conclusion. This fade-out was designed to mimic a natural damping or release effect.

The duration of 1 second was selected as it provided sufficient time for listeners to perceive a representative segment of sound decay without extending the overall length of the listening test excessively. Our observations indicated that emotional characteristics were discernible for very short sounds lasting 0.25 seconds; however, this was primarily evident for mid-register pitches. To ensure that listeners could adequately perceive the details of attack and early decay for lower pitches, we determined that a duration longer than 0.25 seconds was necessary; thus, 1-second tones represented an optimal compromise in length. We concluded that listeners would likely yield similar judgments for sound durations of 1 second or longer.

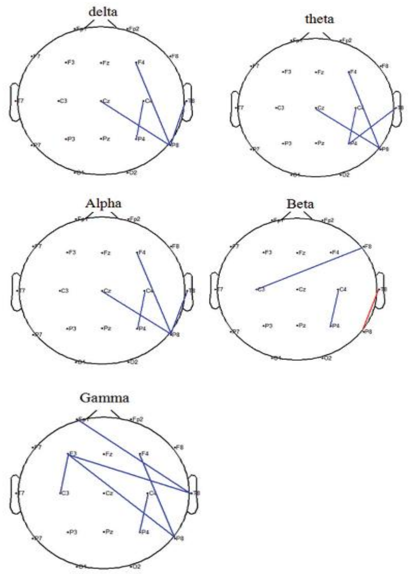

Figure 3. Spectral coherence graph between brain channels in pattern recognition memory in frequency bands.

Blue color shows significant difference lower than 0.05 and red color shows significant difference lower than 0.01

Happy *allegro, gustoso, gioioso, giocoso, content*

Heroic *eroico, grandioso, epico*

Romantic *romantico, appasionato, affetto, afectuoso, passionate*

Comic *capriccio, ridicolosamente, spiritoso, comico, buffo*

Calm *calmato, tranquillo, pacato, placabile, sereno*

Mysterious *misterioso, misteriosamente*

Shy *timido, riservato, timoroso*

Angry *adirato, stizzito, furioso, furibondo, rabbioso, irato*

Scary *sinistro, terribile, allarmante, feroce*

Sad *dolore, lacrimoso, lagrimoso, mesto, triste, mesto, Freddo*

Processing Electroencephalogram Time Series

Block diagram of our proposed method is shown in Figure 4. In this study, we used EEGLAB software, version 13.6.5 to process our EEG signals. After recording EEG signals, the preprocessing step begun. Despite this fact that all the participants tried to be calm during recording EEG signals, but sometimes they blinked or moved, and it was unavoidable, so we used independent component analysis (ICA) method to eliminate artifacts. ICA is a technique which can separate linearly combined sources and in this way detects and eliminates artifacts from EEG signals. This technique can be used for non-Gaussian or dependent sources.

In this research, ICA detected and eliminated blink, muscles, and occipital artifacts [Figure 4]. Blink impresses prefrontal channels (Fp1 and Fp2) so ICA can detect that. If brain activities increase in occipital channels (O2 and O1 channels), ICA detects these activities and we can eliminate occipital artifacts. Moreover, muscle artifacts can be seen in temporal (T7 and T8) and close sites near that so ICA detects that.

Following the preprocessing phase, we employed the SIFT toolbox to compute spectral coherence, a measure of functional connectivity. Initially, we detrended the EEG signals using this toolbox, after which we fitted a model to estimate the connectivity measures. Among the various models available for fitting EEG signals, adaptive multivariate autoregressive (AR) modeling is the most widely utilized approach.

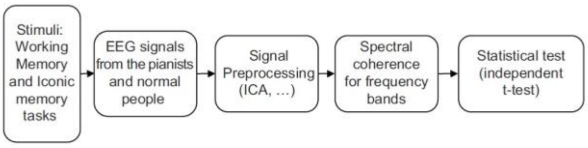

Figure 4. Block diagram of our proposed method

We adopted a modeling approach based on segmented variate autoregressive analysis, which incorporates Fourier transformation and windowing techniques. Additionally, we utilized the Vierio Morph algorithm, which employs a multichannel geometric mean without relying on least squares methods. In this context, two critical parameters were identified: window length and window step size.

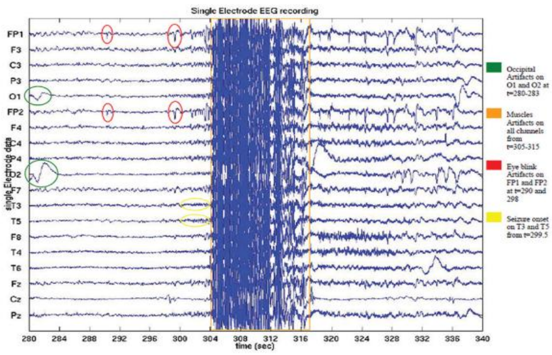

Figure 5. Independent component analysis panel and detected artifacts on electroencephalogram channels

Through a trial-and-error process, we determined the optimal values for these parameters, setting the window length to 3 seconds and the window step size to 1 second. Subsequently, it was necessary to select the model order, denoted as P. The chosen model order should minimize the information criterion known as the Schwarz Bayesian Criterion (SBC).

The SBC is influenced by two key factors i.e. the prediction error and the number of free parameters, which increases with higher model orders.

SBC (also known as Bayes Information Criterion) is computed as: $SBC(p)=\ln(|\Sigma\hat{}(p)|)+p\cdot\ln(T)$. Where, p is the model order, Σ is the number of variables, and T is the total sampling time. In this study, we tried a model order from 1 to 30 and p equal to 9 or 10 and applied this criterion. To evaluate the chosen models, we assessed whiteness, stability, and consistency. The autocorrelation function (ACF) was employed at a significance level of 90% to compute whiteness. Subsequently, coherence was calculated as a measure of connectivity. Additionally, we analyzed the frequency bands of electroencephalogram (EEG) signals, including theta, delta, alpha, beta, and gamma bands, to determine spectral coherence.

2. METHOD

Two distinct sensorimotor paradigms were developed for this investigation: one designated for training and the other for testing. In the actual measurement of event-related direct current electroencephalography (DC-EEG), the auditory and motor features associated with piano playing were systematically dissociated through a probe task paradigm. Conversely, the training procedure was designed to facilitate sensorimotor binding by providing a structured piano-playing environment that included immediate auditory feedback for each keystroke, thereby enhancing the learning experience and promoting effective skill acquisition.

Figure 6. Five-week schedule for the non-musicians

Schematic diagram of the training/testing sessions for the piano practice study. Chronological order of the sessions is top to bottom; order of sub-sessions within one day is left to right.

Spectral Coherence

Coherence serves as a connectivity measure that quantifies the similarity between two signals originating from distinct regions. In the context of electroencephalography (EEG), it specifically assesses the similarity between EEG signals derived from different areas of the brain. This measure evaluates the phase consistency of two signals; when these signals exhibit identical phases—regardless of their amplitude differences—the coherence value reaches its maximum. Thus, coherence can be interpreted as an indicator of temporal or frequency stability across various brain regions. Research has indicated that coherence is linked to cognitive processes such as language acquisition, musicality, and planning.

Emotional Categories

Participants evaluated stimuli based on ten emotional categories: Happy, Heroic, Romantic, Comic, Calm, Mysterious, Shy, Angry, Scary, and Sad. Many of these emotional descriptors are widely recognized and have been documented in previous studies, aligning with the four quadrants of the Valence–Arousal model, as summarized in Table 1. However, it is important to note that variations exist beyond these established categories. The selection of these ten emotional classifications is informed by their frequent usage by composers in tempo and expression markings within musical scores (e.g., terms such as "mysteriously" or "shyly"). Simple English emotional categories were deliberately chosen to ensure familiarity and clarity for lay audiences, contrasting with the traditional Italian musical expression markings commonly employed by classical composers to convey musical character. Our aim was to include a well-balanced set of emotional categories.

Stimulus Generation

The complexity level of real-time synthesized auditory piano patterns is influenced by several parameters: note range, the number of notes concatenated, tempo, and rhythm. An increase in difficulty corresponds with elevated values for these parameters. Furthermore, the generating algorithm adheres to pitch transition probabilities that are characteristic of classical European music.

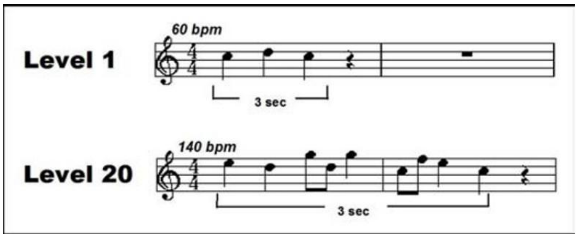

Figure 7. gives two examples for typical stimuli

Statistical Analysis

In this study, we employed independent samples t-tests to examine differences between two distinct groups: professional pianists and non-pianists. This statistical method calculates the means and standard deviations for both groups, allowing us to assess whether significant differences exist based on a predetermined p-value. Prior to conducting the t-test, it is essential to verify the normality of the data distribution. If the data do not conform to a normal distribution, the application of the t-test would be inappropriate. To evaluate this assumption, we utilized the Kolmogorov–Smirnov (KS) test. Following confirmation of normal distribution within our dataset, we proceeded with the independent samples t-test.

DC-EEG Measurement

The event-related direct current electroencephalography (DC-EEG) measurements were designed to differentiate between auditory and motor components of piano performance. The experimental tasks involved an auditory probe task and a motor probe task, which required participants to engage in either passive listening or silent finger movements, thus isolating auditory and motoric processing. After obtaining informed consent from all participants, they were positioned in an optically and acoustically insulated chamber in front of a sight-shaded piano keyboard. During the experiment, only a fixation dot and instructional icons were displayed to guide their engagement with the tasks.

3. RESULTS AND DISCUSSION

We collected pairwise voting results from the participants, which were subsequently analyzed using the Bradley–Terry–Luce (BTL) model to derive rankings based on the number of positive votes each sound received across various emotional categories.

For each emotional category, the BTL scale values for all combinations of dynamics and pitch sum to one. The BTL value assigned to each sound represents the probability that listeners will select that sound when evaluating a specific emotional category. For instance, if all 24 combinations were perceived as equally happy, the BTL scale values would be calculated as 1/24 = 0.0417.

Figure 4 illustrates the BTL scale values for the sounds, accompanied by their corresponding 95% confidence intervals for each sample. In the emotional category of "Happy," there are similar curves across the three dynamic levels.

An observable upward trend in pitch was noted, with the exception of the highest pitches. The overall trend exhibited an arching curve peaking at C6, while lower pitches were associated with less happiness. In contrast, the results for "Sad" demonstrated more pronounced differences between dynamic levels.

Responses were consistently sadder for softer notes, displaying a general downward trend in pitch, where lower pitch ranges elicited the saddest responses. The responses for "Heroic" and "Angry" were comparable; however, loud notes were predominantly associated with feelings of heroism and anger, accompanied by a downward trend in pitch.

The most significant distinction between "Heroic" and "Angry" was that the latter exhibited a strictly monotonic response, whereas "Heroic" did not. The responses for "Romantic," "Calm," and "Shy" were largely similar, with soft notes being most evocative of these emotions and an upward trend in pitch observed. Notably, "Romantic" responses decreased at higher notes (C7 and C8). Conversely, the response curve for "Scary" presented an inverted arch, resembling a mirror image of "Comic." Both the lowest and highest pitches were perceived as scarier, which aligns with previous findings indicating that large variations in pitch significantly enhance ratings for fear. However, differences between dynamic levels in this category were not as pronounced as in most other emotional categories. For "Mysterious," an upward trend in pitch was observed along with relatively similar curves across the three dynamic levels.

To further investigate the effects of pitch and dynamics on BTL scale values within each emotional category, a two-way ANOVA without replication was conducted as shown in Table 1. Prior to this analysis, a Shapiro–Wilk test was performed to assess the normality of the BTL data; only the values for Comic–C1 and Angry–mezzo deviated from normality. Additionally, it is important to note that since there is only one BTL value for each pitch-dynamic pair, the variance within each factor combination (i.e., pitch-dynamic pair) is zero.

Correlation with Acoustic Features

Subsequently, we correlated the continuous BTL scale values with extracted acoustic features using linear Pearson correlation and partial correlation analyses.

Table 1. p-values from ANOVAs and Friedman tests for the effects of pitch and dynamics

Values that were not significant (p ≥ 0.05) are shown in bold.

	Two-Way ANOVA		*Friedman Test*	
	Pitch	Dynamics	Pitch	Dynamics
Happy	0.0000	**0.1770**	0.0051	**0.0724**
Heroic	0.0000	0.0000	0.0058	0.0003
Romantic	0.0000	0.0000	0.0051	0.0003
Comic	0.0000	0.0000	0.0203	0.0015
Calm	0.0060	0.0000	0.0089	0.0003
Mysterious	0.0000	0.0010	0.0086	0.0046
Shy	0.0260	0.0010	0.0084	0.0003
Angry	0.0000	0.0010	0.0041	0.0003
Scary	0.0000	0.0140	0.0044	0.0208
Sad	0.0000	0.0000	0.0106	0.0003

Our previous findings indicated that the correlation between emotional characteristics and instrumental sounds was more pronounced for non-sustaining sounds, as variations in pitch and dynamics were accompanied by corresponding changes in timbre. Specifically, both pitch (measured as the logarithm of the fundamental frequency) and dynamics (quantified as peak RMS amplitude in decibels) exhibited significant correlations with eight distinct emotional categories. Notably, seven of these emotional categories demonstrated correlations with nearly all analyzed features, with the exceptions being Comic, Scary, and Sad. This observation can be attributed to the unique waveform shapes associated with each category: Comic displays an arching contour, Scary exhibits a bowl-like form, and Sad is characterized by somewhat oscillatory curves.

Only four emotional categories showed significant correlations with half or more of the examined features. The most notable variations were observed in the Heroic and Shy categories, suggesting that these emotions are strongly influenced by pitch and dynamics while being less affected by temporal and spectral envelope features compared to other emotional categories. In contrast, the Scary and Comic categories exhibited a marked increase in the number of significant features when the influences of pitch and dynamics were controlled for, highlighting their heightened sensitivity to temporal and spectral envelope characteristics.

The primary objective of this study was to investigate how the emotional attributes of piano sounds fluctuate in relation to pitch and dynamics. Addressing the original research questions posed in this paper, we found that:

- All ten emotional categories were significantly influenced by pitch.

- The emotions Happy, Romantic, Calm, Mysterious, and Shy generally increased with rising pitch, although a decrease was occasionally noted at the highest pitches.
- The emotions Heroic, Angry, and Sad typically decreased with increasing pitch, albeit at varying rates.
- Comic exhibited its strongest expression in the mid-register while demonstrating diminished intensity at both the highest and lowest registers.
- Scary was most pronounced in both the lowest and highest registers.

In terms of dynamics:

- Nine emotional categories were significantly impacted by dynamics.
- The emotions Heroic, Comic, Angry, and Scary were particularly pronounced during loud notes.

These findings underscore the complex interplay between pitch, dynamics, and emotional expression in piano music.

4. CONCLUSION

In recent years, neuroscience has made significant advancements, particularly in the study of how various factors influence memory. A notable achievement in this field is the assessment of music's role in human life and its effects on behavior.

This study investigates the spectral coherence of professional pianists compared to non-pianists through the application of memory assessments, specifically the Spatial Working Memory (SWM) and the Pattern Recognition Memory (PRM) tests. Following the processing of electroencephalogram (EEG) signals from both groups using suitable filtering techniques, we computed the spectral coherence values for pairs of electrodes. Significant differences between the two groups were identified through independent samples t-tests. Our findings reveal notable distinctions in the EEG signals of pianists versus non-pianists, which can be attributed to the influence of musical training on brain activity. Additionally, we identified specific brain regions—namely, the temporal, parietal, and central areas—that exhibited differential activation between the two groups. These regions are associated with acquired skills, language perception, and play a crucial role in memory and cognitive functions.

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