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Exploring approaches to compare emotional responses to the same stimuli from different individuals

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Abstract: Understand human emotional behavior is a challenging yet crucial endeavor for enhancing user experience through the application of Affective Computing techniques. These methods have the potential to foster more natural and emotionally responsive interactions between users and systems. In a multicultural world, it is equally important to understand the varied emotional responses individuals have to a same stimuli, ensuring that software adaptations and interventions are appropriately tailored. This study examines two methodologies for comparing how individuals from diverse backgrounds react emotionally to the two audiovisual stimulus. By utilizing data analysis and machine learning tools, the study aims to explore whether two individuals react similarly to a same stimulus. Alongside an exploration of the unique features of each approach, the research validates these methods by analyzing the emotional responses of 39 participants, identifying both commonalities and differences. The findings not only underscore the approaches' effectiveness but also highlight their potential for complementing one another.

Keywords: Affective Computing, Facial Expressions, Comparison of emotional responses

1 Introduction

In a context where human emotions have received growing attention in the design and use of interactive systems, it is imperative to understand how people emotionally respond to the stimuli presented to them [van Erven and Canedo, 2023; D'Amelio *et al.*, 2023]. The benefits inherent to this knowledge can encompass applications aimed at entertainment, such as streaming platforms, as well as distance learning systems [Pei *et al.*, 2024], where the interaction between teachers and students often involves audiovisual content. In such situations, understanding how individuals have reacted to the content can provide valuable insights by highlighting positive aspects of audiovisual productions and identifying areas for improvement to ensure the resource achieves its intended purpose. Additionally, it can reveal instances where students experience difficulties in assimilating the content [D'Avila Goldoni *et al.*, 2023].

Even though technological advancements have facilitated the development of increasingly efficient techniques and algorithms for emotion recognition, numerous challenges remain to be overcome in the interpretation of emotional data, particularly when associated with audiovisual content. As highlighted in the field of Human-Computer Interaction [Barbosa *et al.*, 2021], the interaction process is strongly influenced by the context of use. Unlike products such as service or product applications that seek to offer users a positive experience, audiovisual productions may aim to provoke emotions typically perceived as negative in their viewers. Hence, emotions such as anger or fear are not indicators of a bad experience, as in many computational applications, but rather indicators that the user is engaged with the content. Examples of this category include drama, thriller, and horror films. In the field of Education, the emotional state of confusion may reflect the student's effort in learning; however, a prolonged duration of this emotional state may lead to frustration [D'Avila Goldoni *et al.*, 2023].

In addition to contextual aspects, it is also known that an individual's emotions are susceptible to demographic factors [Cowen *et al.*, 2020; Fan *et al.*, 2021] and their individual differences, such as personality traits [Judge and Robbins, 2017; Reisenzein *et al.*, 2020; Kutt *et al.*, 2020]. Therefore, a single stimulus may elicit distinct emotional responses in different individuals. It is also possible that this stimulus evokes no emotion in a subset of individuals. Hence, merely exposing an individual to a stimulus does not guarantee the elicitation of specific emotional states.

In the field of Affective Computing, there is growing interest among researchers in developing applications that adapt to users' emotional states [Assunção and Neris, 2019; Pei *et al.*, 2024; Guimarães and De Almeida Neris, 2024]. Generally, the proposed solutions involve training Machine Learning algorithms on large datasets, which do not always consider the contextual characteristics of the interaction process and may also overlook similarities or particularities of the individuals comprising the training data. In this complex context, understanding how different people emotionally respond to a stimulus is essential for improving Affective Computing solutions while considering principles of explainability.

More than associating a user's emotional reactions with experience categories such as good/bad or engaged/disengaged, it is crucial to understand why some people emotionally respond to a stimulus while others do not. It is also necessary to identify which individuals respond similarly to the same stimuli and which respond differently. Furthermore, it is essential to develop methods to compare these emotional reactions.

While the process of identifying similarities is not novel and is embedded in various solutions involving the use of Machine Learning algorithms, it is also true that this process is not always addressed with transparency and a focus on interpretability. To address this gap, in [Aguiar *et al.*, 2024] we discussed two approaches for comparing the emotional responses of different individuals. In this previous study, we analyzed the application of these approaches to compare the emotional responses of 39 individuals to a disgust stimulus.

This paper is an extended version of that study, incorporating responses to a surprise stimulus. By examining the emotional reactions of 39 individuals to two audiovisual stimuli (disgust and surprise), the study highlights the specific characteristics of each approach. It is important to clarify that this work does not aim to propose or evaluate new emotion recognition techniques. Rather, it focuses on comparing the emotional responses elicited by the same audiovisual stimuli across different individuals, using data extracted by an existing recognition tool. The emphasis, therefore, lies on analyzing the distinctive features of each approach and on demonstrating how they can be interpreted and assessed, thereby underscoring the added value of an integrated analysis that combines the two proposed methods.

2 Backgrond and contributions of this paper

Studies discussing individuals' emotional reactions to audiovisual stimuli are not novel in the literature and can be classified according to the investigation's objective. An exploratory review of the literature reveals a larger number of studies aimed at **detecting engagement or interest** in audiovisual content based on users' emotional responses. As an example of this practice, the research by Oakes *et al.* [2024] investigates the feasibility of using facial expression data, recorded non-invasively, to assess audience engagement in artistic performances. Unlike studies that analyze each user's data separately, this research assumes that the similarity of the audience's emotional responses is an indicator of engagement with the performance. This premise emerges from previous studies that observed similar user reactions while they were engaged in listening to music.

In this context, a study conducted by de Sá *et al.* [2023] analyzed the emotional responses of 10 users to a horror movie trailer that, at the time of the study, had not yet been released. The objective was to predict the intention to watch the movie. Electroencephalogram (EEG) signals were observed, and, using eye tracking, the region of the video each user was looking at was recorded. Although the results indicate patterns in emotion recognition, there is no information regarding the similarity of emotional responses from different individuals. In a similar study conducted by Da Silva *et al.* [2022], also using EEG and eye tracking techniques, users' emotional reactions to audiovisual content were observed to support the evaluation of users' perceptions of the content viewed.

Regarding the **comparison of similarity in emotional responses**, Bakker *et al.* [2020] describe a study in which two groups of people, one consisting of individuals with a liberal political profile and the other with a conservative profile, had their emotional responses to visual stimuli recorded using facial electromyography. Individuals from both groups were exposed to a set of images. At the end of the process, the researchers applied Student's t-test to identify whether there was a significant difference between the data from the different groups. The results, reported in Bakker *et al.* [2022], reveal that there was no statistically significant difference between the two groups of users.

The literature also reveals **challenges** inherent to emotional analysis based on audiovisual stimuli. Although the use of films to elicit emotions in users has proven to be an effective approach for both positive and negative emotions Fernández-Aguilar *et al.* [2019], there are cases where emotional impacts are subtle. For example, analyses by Boğa *et al.* [2022] revealed that, contrary to expectations, the videos used as stimuli were not capable of generating equivalent emotional responses. In some cases, the indices identified for certain facial expressions associated with emotions were very low. As a possible justification, the authors explained that participants had been instructed not to look at the screen during uncomfortable moments (possibly in compliance with ethical procedures). As a result, the software used for facial expression recognition may not have adequately identified expressions at those moments.

A complementary line of research is presented by Hu *et al.* [2022], who investigate individual differences in emotional experiences through a 'profile' perspective, combining self-reported multidimensional ratings and EEG data. Their study introduces the concept of emotion profiles as context-dependent blends of multiple emotions elicited by a variety of audiovisual stimuli. Using inter-subject representational similarity analysis (IS-RSA), they found that participants with similar emotional profiles exhibited similar patterns of neural activity, particularly in the delta and theta bands. While their work provides valuable insights into the neural underpinnings of emotional variability, it relies on self-assessment and neurophysiological data, requiring controlled environments and specialized equipment.

Our study offers a distinct yet complementary contribution by proposing two computational approaches to compare emotional responses based solely on facial expression data. Unlike previous studies that analyze individual responses in isolation or emphasize classification accuracy, we focus on synchronized, stimulus-driven comparisons between participants. This dual-perspective framework enables a deeper understanding of both the emotional states experienced and the temporal evolution of these states, using data that can be unobtrusively collected and interpreted in real-time. Such methodological flexibility broadens the applicability of emotional comparison techniques in practical scenarios, such as adaptive educational systems or affective media analysis.

From the analysis of the aforementioned studies, we identified a broad range of opportunities for advancing research on the comparison of emotional responses from different individuals exposed to the same stimuli, underscoring the relevance of the present investigation. This study contributes by proposing a categorization of approaches for emotional data comparison, which is presented in Section 3. While much research in Affective Computing focuses on enhancing the accuracy of emotion recognition algorithms, our work lies outside this scope. We assume the availability of emotion recognition outputs and investigate how such data can be leveraged to compare emotional responses across participants. The results obtained from comparing the emotional reactions of 39 individuals, whose methodological process is detailed in Section 4, provide insights into the distinctive characteristics of each approach and advance the understanding of similarities in emotional responses.

3 Approaches to compare emotional responses

Real-time emotion recognition techniques (whether physiological or not) collect a large amount of data over a given period. As a consequence, processing and interpreting this large dataset can be a complex process, achievable in different ways. Based on critical reflection regarding the practices adopted in the literature for interpreting data related to emotional states, two approaches applicable to this context are proposed below.

3.1 Emotional Experience Analysis

The first approach, referred to in this study as "Emotional Experience Analysis" (EEA), considers the emotions elicited by an individual during a given period. From this perspective, the focus is on understanding users' emotional responses to stimuli, as well as the frequency or intensity at which these emotions were detected.

Figure 1 illustrates, in a simplified manner, how emotional experience analysis is characterized. In this figure, there is a visual representation of a timeline, with markings indicating different segments of a video. Below, there are two tracks, each representing a different user. On each user's track, in the region corresponding to each video segment, there is a visual representation of the emotion experienced by the user during that moment. The figure reveals that two individuals, denoted by the nicknames "Person A" and "Person B", had facial expressions associated with recognized emotions in two segments of the video. While Person A displayed a facial expression associated with anger in the first segment, the emotion identified in the second segment was joy. The opposite process is observed for Person B, who starts the video with a facial expression associated with joy and concludes it with a facial expression associated with anger.

When applying emotional experience analysis, the experiences of users A and B will be considered equivalent, since, during the analysis process, the two emotions were observed with equal intensity. Therefore, it is noted that in this approach, the order in which emotions manifest is not relevant, but rather the frequency or intensity with which they occur. Following this approach, the conclusion would indicate that the video elicited emotional reactions of joy and anger in both users. From concept to implementation, the following techniques can be applied in this context: i) calculation of the average emotions; ii) quantification of the most intense facial expression during a given period; iii) calculation of Euclidean distance; and iv) clustering algorithms, such as *kNN*. Examples of studies adopting such practice include those by González-Rodríguez *et al*. [2020] and Boğa *et al*. [2022].

3.2 Emotional Trajectory Analysis

Unlike the previous approach, which disregards temporality in emotional behavior, Emotional Trajectory Analysis (ETA) focuses on observing whether, over a given period, the intensity with which an emotion was identified increased or decreased over time. This approach emphasizes the impact of video events on users' emotional states. Referring again to Figure 1 for exemplification, it can be understood that, for Person A, the first segment of the video elicited the emotion of anger, while the second segment elicited the emotion of joy. Conversely, the opposite situation can be observed for Person B. At this point, an important issue arises: the same dataset can generate different interpretations depending on the analysis approach. While the previous approach led to the conclusion that both users had equivalent experiences, the current approach highlights that these users had completely distinct experiences, as evidenced by Figure 1.

In practical terms, emotional trajectory analysis can be observed through correlation. In this context, one challenge lies in defining the time window during which the similarity between two users will be analyzed. In Oakes *et al*. [2024], for example, the option was to analyze the correlation of emotional states of different users within a one-minute time window.

To highlight the conceptual and operational distinctions between EEA and ETA, Table 1 presents a side-by-side comparison of their main characteristics.

4 Materials and methods

In order to compare and validate approaches to identify similarities in emotional responses of different individuals, the EAA and ETA approaches, presented in the previous section, will be applied. To guide the methodological path of this study, the following research questions were defined:

- **RQ1**: Are there similar emotional experiences among individuals who watched the same audiovisual stimulus?
- **RQ2**: For the same audiovisual stimulus, are there individuals with similar emotional trajectories?
- **RQ3**: Are there cases of individuals who exhibit similarity or distinction in both experience and emotional trajectory?

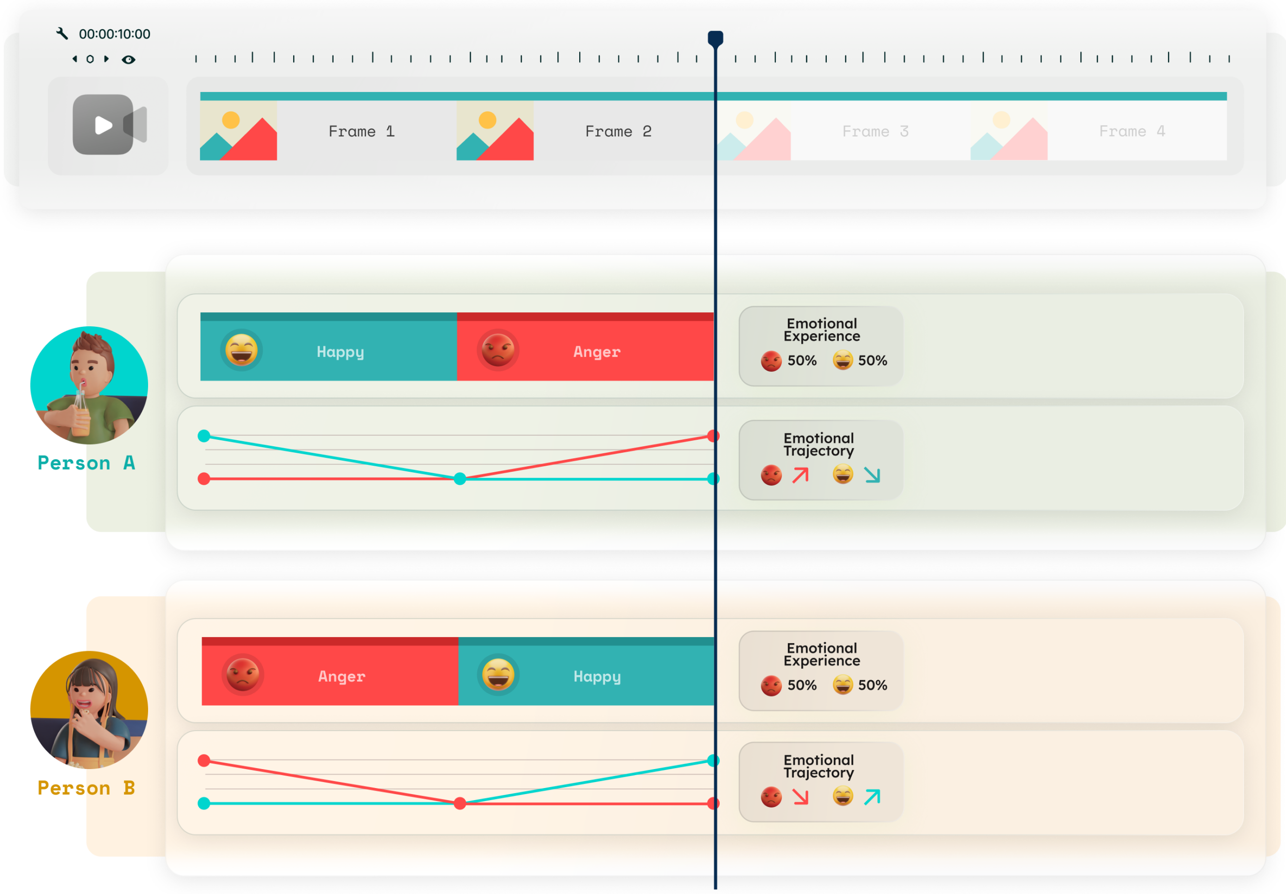

Figure 1. Representation of the data interpretation process according to the EEA and ETA approaches, where the emotional reactions of each user to different segments of the same audiovisual stimulus are compared. Image made using Freepik pictures.

To answer **RQ1**, similarities in emotional experiences of different users in response to the same audiovisual stimuli will be analyzed, according to the AEE approach described in Section 3.1. To reduce the sample size, a feature vector will be generated for each individual (V_i), containing the mean intensity of each facial expression associated with emotion. The following order was established: neutral (μ_1), joy (μ_2), sadness (μ_3), anger (μ_4), fear (μ_5), disgust (μ_6), and surprise (μ_7).

$$V_i = [\mu_1, ..., \mu_n] \quad (1)$$

Next, the data will be submitted to the kNN (*k-Nearest Neighbors*) algorithm, with parameter $n = 39$, to enable the comparison of all pairs of individuals. Thus, for each pair, the distance between these individuals will be calculated. To address **RQ2**, which deals with emotional trajectory (ATE approach, described in Section 3.2), the correlation between users' emotional trajectories will be calculated. Given the data distribution, the correlation method used will be Spearman's correlation. Since correlation compares the variation between two variables, the correlation will be calculated considering the neutral facial expression. For the discussion, only statistically significant correlations ($p < 0.05$) will be considered. Finally, for the discussion of **RQ3**, the correlation index (ρ_s) and the kNN similarity index will be jointly analyzed for user pairs.

4.1 Dataset selection

Although there are several datasets of facial expressions associated with emotions, datasets containing videos or photographs of people reacting to the same set of audiovisual stimuli, with temporal synchronization, are scarce. After exploratory research, two datasets containing such characteristics were identified: *AM-FED*, maintained by Affectiva, and the Emognition Wearable Dataset 2020 Saganowski *et al.* [2021]. Both datasets are free for scientific research, which was another selection criterion. In this sense, the authors requested access to the producers of the *Emognition* dataset and *AM-FED*. At the time of writing, only the producers of the *Emognition* dataset responded.

The *Emognition*[1] dataset gathers data from 39[2] participants (18 male and 21 female, aged 21 ± 2 years). According to Saganowski *et al.* [2021], the participants were recruited through advertisements posted on a social network. All participants in the study were Polish and spoke the local language, and they were also aware that the data would be shared with other researchers. Each volunteer watched ten videos. One was considered neutral, while the other nine evoked a specific emotion. The data collection proto-

[1] `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/R9WAF4`. Access on 05 October 2025.

[2] The number of 39 participants considers only individuals for whom image records are available.

Table 1. Comparison between EEA and ETA approaches.

Aspect	Emotional Experience Analysis (EEA)	Emotional Trajectory Analysis (ETA)
Focus	Identifies the average emotional states experienced by each user during the stimulus	Examines the temporal variation of emotional responses throughout the stimulus
Temporality	Not considered, since this approach is based on aggregated values	Considered; emotions are analyzed over time
Metric used	Mean intensity of facial expressions; Euclidean distance; clustering (e.g., kNN)	Correlation between time series of facial expression intensity (e.g., Spearman's rho)
Interpretation	Similarity based on which emotions were felt and how intensely	Similarity based on how emotions evolved over time
Sensitivity to sequence	Ignores the order of emotional reactions	Sensitive to the sequence and transitions of emotional states
Use case example	Classifying users who share dominant emotions during a film	Identifying users whose emotional engagement follows similar patterns

col involved the following procedures: at the beginning of the collection, for five minutes, volunteers watched a video containing lines and dots on a black screen. They then answered a self-assessment questionnaire. For each of the ten stimulus videos, the following steps were taken: i) 2-minute video containing lines and dots on a black screen; ii) video intended to evoke a specific emotion (lasting 1 to 2 minutes); and iii) self-assessment questionnaire response. In addition to the recorded videos, the dataset comprises facial expression recognition data analyzed using Quantum Sense software, which recognizes facial expressions associated with the following emotions: anger, disgust, joy, sadness, and surprise, as well as the neutral face. As the records provided in the dataset were not associated with the video frame, to ensure analysis compatibility, the videos were reprocessed by the authors of this study. For this study, due to scope limitations, users' emotional reactions to stimuli associated with disgust and surprise were considered.

4.2 Ethical issues

Regarding ethical aspects, Resolution No. 674/2022 of the Brazilian National Health Council (CNS) permits the development of research using pre-existing datasets without the need for approval by a Research Ethics Committee. In the case of this study, we used a dataset collected and made available by Saganowski *et al.* (2021). As reported by the authors, the original data collection was approved by the Ethics Committee of Wroclaw Medical University (Poland), under approval no. 149/2020. Participants provided written informed consent, in which they acknowledged their awareness of the study's purpose and procedures, and explicitly agreed to the collection, storage, and sharing of their data with other researchers.

4.3 Data processing

The videos in the *Emognition* dataset were organized with user identification and the stimulus used in that collection. At the beginning of the processing phase, for each video file, static images were extracted, one per second of video duration. Thus, a 120-second video resulted in 120 static images. This process aimed to reduce data dimensionality. The images were then processed using the *Face-api.js* library, whose effectiveness in recognizing facial expressions associated with emotions was evaluated in a previous study by Aranha *et al.* [2021] and was also adopted by Zhou *et al.* [2022] and Vora *et al.* [2023]. For each image, the library returns a vector with the intensity of each of the seven facial expressions: neutral, joy, fear, disgust, anger, sadness, and surprise. It is important to note that, unlike some solutions that analyze the occurrence of facial expressions independently, *Face-api.js* considers the occurrence to be mutually exclusive. If a neutral facial expression is detected with 80% intensity in a given image, the indices related to other facial expressions must sum to 20%. Therefore, the neutral facial expression indicates emotional evocation at a given moment. For each user, in each stimulus, a CSV (*comma-separated values*) file was generated containing the emotional intensity vector for each image. The image number was also recorded to facilitate the comparison of emotional responses among different users.

5 First study: analyzing emotional responses to disgust stimulus

In this section, considering the methodological processes described in Section 4, the results of applying two approaches to compare the emotional responses of 39 individuals to the audiovisual disgust stimulus will be presented.

5.1 Detection of similar emotional experiences

To identify similarities in the emotional experiences of different individuals (**QP1**), the average intensity of each facial expression was calculated for each participant. Thus, a vector of seven features was obtained for each individual. Figure 2 presents, in this context, a scatter plot of the emotional data of these individuals[3]. To generate the figure, due to the need to reduce dimensionality from seven to two, a PCA (Principal Component Analysis) algorithm was applied. Figure 2 shows, based on the proximity of the points, that there is a considerable number of individuals who exhibited similar emotional experiences. Conversely, there are individuals with distinct emotional experiences.

[3]To ensure reproducibility, the individuals are identified by the code used by the authors of the *Emognition* dataset.

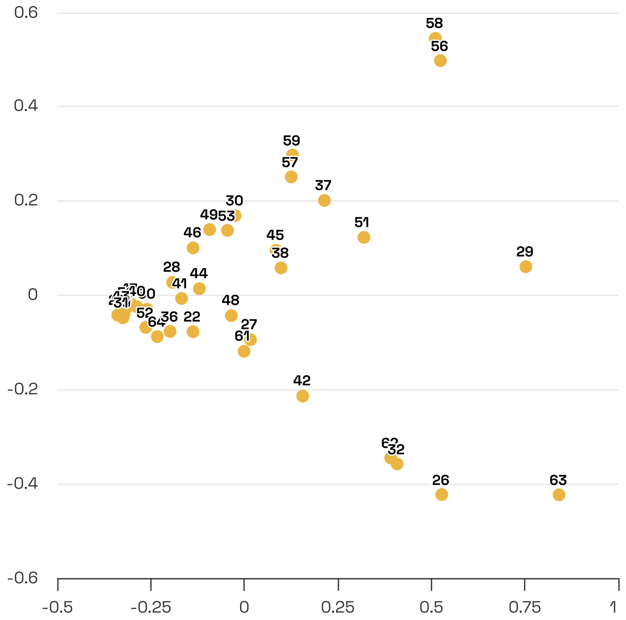

Figure 2. Dispersion of individuals regarding facial expressions collected during the audiovisual disgust stimulus.

Individual	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7
36	0.89	0.09	0.02	0.00	0.00	0.00	0.00
64	0.92	0.08	0.00	0.00	0.00	0.00	0.00
28	0.85	0.00	0.07	0.00	0.01	0.00	0.06
63	0.07	0.82	0.10	0.00	0.00	0.01	0.00

Table 2. Comparison of feature vectors of two pairs of individuals, considering their reactions to the disgust stimulus.

To enrich the data interpretation process, two pairs of individuals were arbitrarily selected from the dispersion presented in Figure 2 for more detailed analysis: one graphically close pair (individuals 36 and 64) and one graphically distant pair (individuals 28 and 63). The data, presented in Table 2, highlight the similarity of the feature vectors of individuals 36 and 64, as well as the difference between the feature vectors of individuals 28 and 63. While the first pair exhibited a high incidence of neutral facial expressions, with a similar occurrence of facial expressions associated with happiness, the second pair had distinct experiences. Individual 28 had a higher incidence of neutral facial expressions, while individual 63 had a higher incidence of facial expressions associated with happiness.

Next, the *kNN* algorithm was also applied to calculate the distance between individuals in each pair. The closer the index is to zero, the greater the similarity identified between two users. Due to the high number of combinations (1482, with $n = 39$), Table 3 presents the five pairs with the greatest similarity, followed by the five pairs with the least similarity.

Enhancing the analysis and fostering an understanding of the entire scenario, Figure 3 presents a distribution graph of the distance indices calculated for each pair of users using the *kNN* algorithm. As can be observed, there is a significant number of occurrences with high similarity between individuals.

Individual	Neighbor	Distance
31	39	0.00
25	24	0.00
47	50	0.01
43	24	0.01
43	23	0.01
24	63	1.24
63	24	1.24
63	25	1.24
23	63	1.23
43	63	1.23

Table 3. Results from the kNN algorithm for the disgust stimulus.

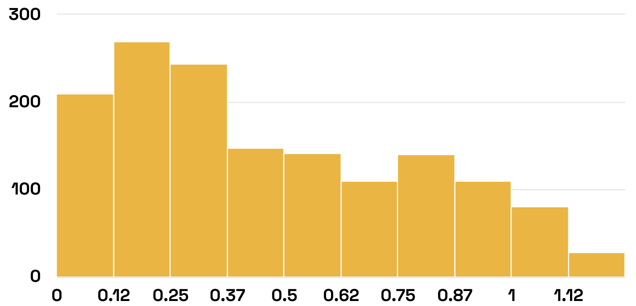

Figure 3. Distribution of similarity indices calculated by the *kNN* algorithm for the disgust stimulus.

5.2 Identification of similar emotional trajectories

Considering **QP2**, which addresses the identification of similarities in emotional trajectories of different individuals in response to the same audiovisual stimuli, the Spearman correlation was calculated for each pair of users. This operation was performed for the indices related to neutral facial expressions, considering the reasons presented earlier in Section 4. A total of 210 statistically significant correlations ($p < 0.05$) were found. Of these, 67 correlations were negative and 143 were positive. To aid the process of data comprehension and validation of this approach, graphical resources were used.

Figure 4 presents an overview of the categorization of correlation indices, considering strength and direction criteria. The majority of significant correlations show a positive direction and moderate strength (46%). Next, representing 20% of occurrences, are correlations classified as having a positive direction and weak strength. Correlations with a negative direction showed an equal number of occurrences for moderate and weak strengths, each representing 15%. It is also worth noting that correlations classified as strong, regardless of direction, showed a low number of occurrences. Of these, 8 are positive and 2 are negative.

The analysis of correlation indices suggests that, in the context of the audiovisual disgust stimulus, there is a greater tendency for facial behavior related to neutral facial expression to become moderately similar over time, with few cases in which different individuals exhibited opposing trajectories, although this phenomenon did occur.

Table 4 presents the correlation indices between some pairs of individuals, highlighting positive correlations. The table shows a sample of ten records, ordered according to the

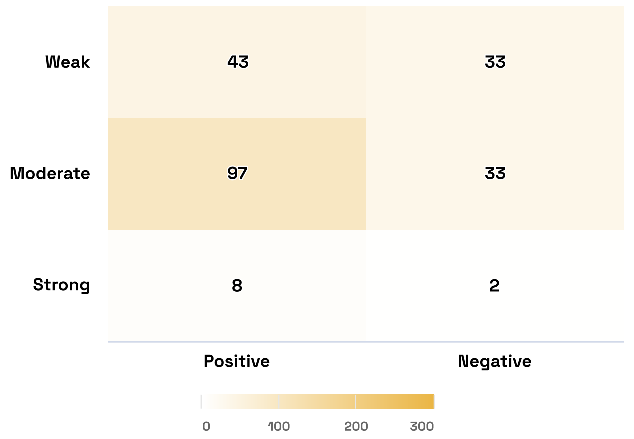

Figure 4. Categorization of correlation indices by strength and direction, calculated for reactions to the disgust stimulus.

correlation index. The first five rows show the initial records, while the last five present the final records.

Individual 1	Individual 2	ρ_s	p
50	43	0.97	0.00
47	43	0.97	0.00
47	50	0.96	0.00
50	60	0.84	0.0
60	43	0.82	0.00
56	29	0.24	0.04
50	27	0.24	0.04
28	26	0.24	0.04
26	31	0.24	0.04
51	57	0.25	0.03

Table 4. Correlation indices between pairs of users for the disgust stimulus.

To enhance data comprehension, Figures 5, 6, and 7 present line graphs comparing, longitudinally, the variation in neutral facial expression intensity of two users. In the case of Figure 5, a comparison is made between users identified by numbers 38 and 48. Although the intensity of neutral facial expression of both users varied over time, there is a moderate and significant positive correlation ($\rho_s = 0.54$, $p = 0.0$), evidenced by the longitudinal similarity in line behavior. When analyzing Figure 6, which illustrates the comparison for users 43 and 47 over the same time interval covered by Figure 5, it initially becomes evident that the facial behavior of the second pair of individuals showed little variation compared to the previous pair. These users did not exhibit notable emotional activation in their facial expressions for a considerable part of the video but showed a strong correlation ($\rho_s = 0.97, p = 0.0$).

Moreover, although the research question driving this discussion addresses the identification of similar trajectories, the approach is also capable of revealing opposing emotional trajectories through the analysis of negative correlations. Figure 7 presents a situation where there was a moderate negative correlation ($\rho_s = -0.65, p = 0.0$) between users 43 and 63.

5.3 Comparison between approaches

In order to discuss **QP3**, which addresses the occurrence of similar emotional experiences and trajectories, the results of the *kNN* algorithm were compared with Spearman's correlation. Table 5 presents ten records. For sample representation, the following were selected: i) the first five records with positive correlation, ordered in descending order by the correlation index and in ascending order by distance; ii) the first five records with negative correlation, ordered in descending order by the correlation index and in ascending order by distance.

Individual	Neighbor	ρ_s	p	kNN
50	43	0.97	0.0	0.01
47	43	0.97	0.0	0.03
47	50	0.96	0.0	0.01
50	60	0.84	0.0	0.06
60	43	0.82	0.0	0.07
47	63	-0.76	0.00	8.07
50	63	-0.72	0.00	8.04
63	43	-0.65	0.00	7.99
27	26	-0.61	0.00	7.01
49	32	-0.57	0.00	6.10

Table 5. Correlation indices and distance between pairs of individuals, considering the EAA and ETA approaches, for the disgust stimulus.

For exemplification of the results, two pairs of individuals will be discussed in detail: 43-50 and 47-63. The first pair, consisting of individuals identified by numbers 43 and 50, is characterized by high similarity in both approaches to identifying emotional similarity. A review of facial expression data reveals that, for both individuals, the audiovisual stimulus did not provoke significant manifestation of facial expressions associated with emotions detected through the use of *software*, as shown in Table 6. The analysis is corroborated by Figure 8, which highlights strongly similar behavior.

Individual	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7
43	0.99	0	0.01	0	0	0	0
50	0.98	0	0.02	0	0	0	0
47	0.97	0	0.03	0	0	0	0
63	0.07	0.82	0.1	0	0	0.01	0

Table 6. Comparison of feature vectors of two pairs of individuals based on integrated analysis of EAA and ETA for the disgust stimulus.

Conversely, the comparison between the two approaches also facilitates the identification of pairs of individuals with significant distinctions, both in the EAA and ETA approaches, as is the case for the pair consisting of individuals 47 and 63. As indicated in Table 6, it is noted that while individual 47 predominantly exhibited a neutral facial expression, individual 63 showed a higher incidence of facial expressions associated with joy. Similarly, Figure 7 illustrates the ETA comparison for these two individuals, revealing the distinction between their reactions throughout the video, as

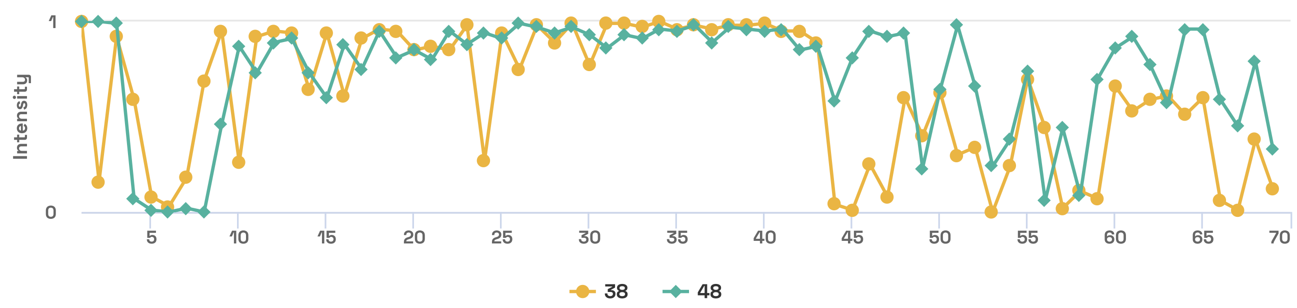

Figure 5. Graphical comparison of the emotional trajectory of individuals 38 and 48, with moderate correlation ($\rho_s = 0.54$, $p = 0.0$) for the disgust stimulus.

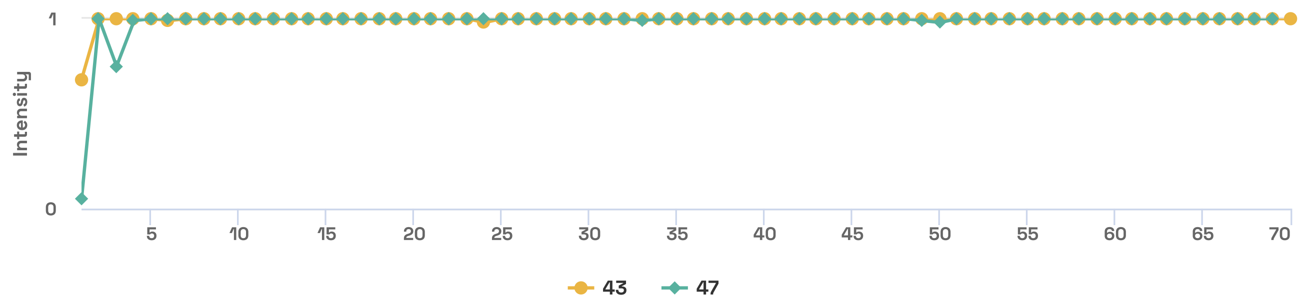

Figure 6. Graphical comparison of the emotional trajectory of individuals 43 and 47, with strong correlation ($\rho_s = 0.97$, $p = 0.0$) for the disgust stimulus.

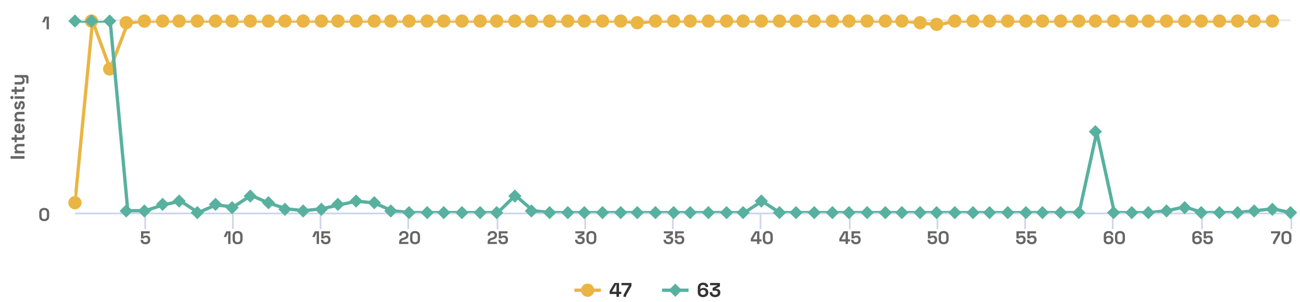

Figure 7. Graphical comparison of the emotional trajectory of individuals 47 and 63, with moderate and inverse correlation ($\rho_s = -0.65$, $p = 0.0$) for the disgust stimulus.

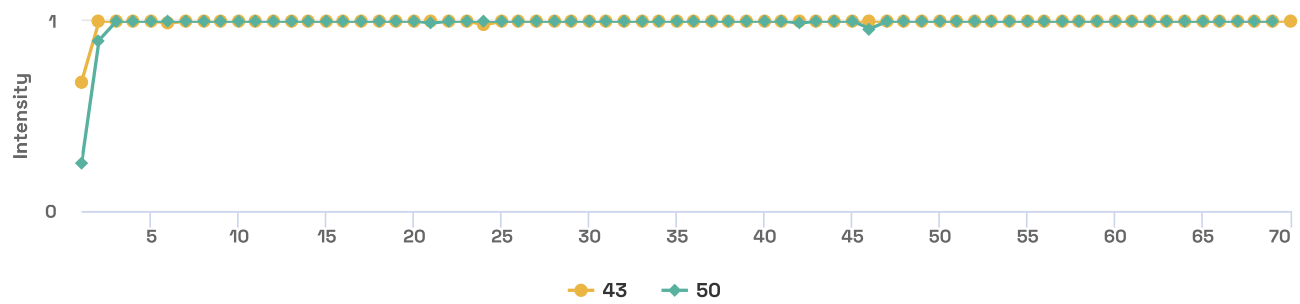

Figure 8. Graphical comparison of the emotional trajectory of individuals 43 and 50, with strong and positive correlation. ($\rho_s = 0.97$, $p = 0.0$) for the disgust stimulus.

previously discussed.

6 Second study: analyzing emotional responses to surprise stimulus

Similarly to the previous section, the results derived from the application of two approaches for comparing emotional responses will be presented, this time for the audiovisual surprise stimulus.

6.1 Detection of similar emotional experiences

Figure 9 presents a scatter plot generated after the application of the PCA algorithm, providing a visual representation of the similarities between individuals in the analyzed dataset.

From the analysis of the graph, it is evident that there is a large number of individuals grouped in close positions, while others stand out by deviating from the concentration. Examples of such cases include individuals identified by numbers 58, 29, and 51, who appear far from most of the individuals represented in the graph. At this point, it can be inferred that most of the individuals experienced similar emotional responses, with few distinct emotional experiences.

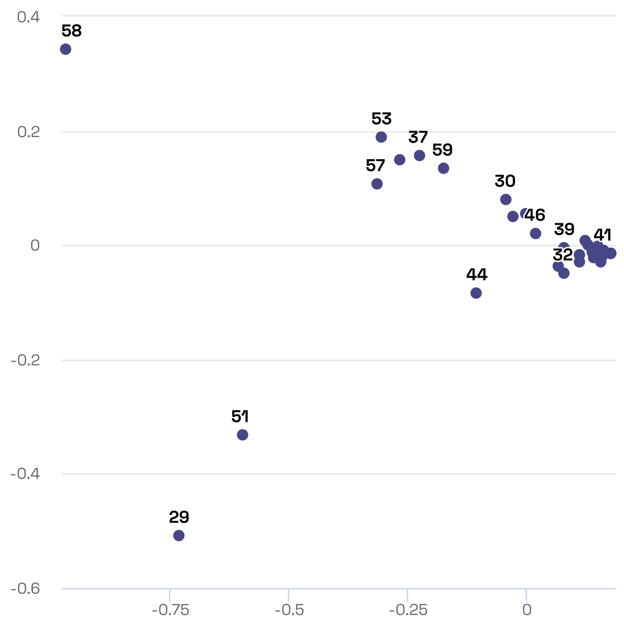

Figure 9. Dispersion of individuals regarding facial expressions collected during the audiovisual surprise stimulus.

As presented in the previous study, pairs of individuals were selected for observation of the feature vector based on the scatter plot. Table 7 presents a comparison of the facial expression averages of individuals 32, 39, 29, and 58. While individuals 32 and 39 are positioned close to each other on the graph, individuals 29 and 58 are positioned at the vertical extremes of the graph. From the analysis of each individual's feature vector, it is observed that volunteers 32 and 39 had similar indicators, with the neutral facial expression (μ_1) predominating. On the other hand, users 29 and 58 presented distinct experiences, with emotions represented by μ_2 and μ_3, respectively, predominating.

Individual	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7
32	0.91	0.06	0.02	0.00	0.00	0.00	0.01
39	0.93	0.00	0.04	0.00	0.00	0.00	0.03
29	0.12	0.64	0.07	0.00	0.16	0.00	0.00
58	0.09	0.01	0.77	0.00	0.00	0.12	0.00

Table 7. Comparison of feature vectors from two pairs of individuals, considering their responses to the surprise stimulus.

To complement this analysis, Table 8 shows the similarity index, calculated using the kNN algorithm. From the table, it is evident that there are individuals with complete similarity (for example, individuals 42 and 22). For this pair, there was no emotional response to the stimulus video, and the neutral facial expression was consistently detected.

Individual	Neighbor	Distance
42	22	0.00
43	31	0.00
43	55	0.00
50	63	0.00
43	22	0.00
43	58	1.20
41	58	1.20
42	58	1.20
58	22	1.20
58	23	1.20

Table 8. Results from the kNN algorithm for the surprise stimulus.

Finally, Figure 10 shows the histogram of the distances calculated by the kNN algorithm for the emotional responses of pairs of individuals to the surprise stimulus. The figure reveals a higher density of pairs that exhibited high similarity (distance less than 0.12), exceeding 600 pairs of individuals with this degree of similarity.

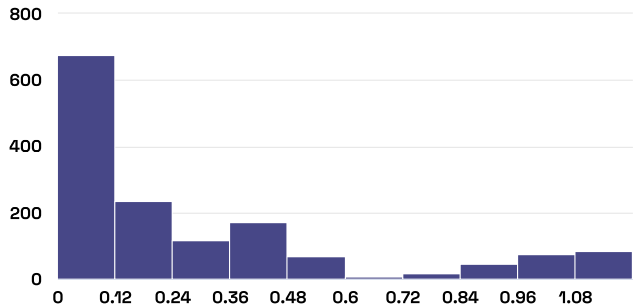

Figure 10. Distribution of the similarity index calculated by the *KNN* algorithm for the surprise stimulus.

6.2 Identification of similar emotional trajectories

Regarding the QP2 question, which concerns the analysis of similar emotional trajectories, Spearman correlations were calculated for pairs of individuals. In this process, 94 statistically significant correlations were found ($p < 0.05$). Figure 11 shows the categorization of the correlations, classified by strength and direction. From the analysis of the figure, it is observed that moderate correlations predominate, representing 87% of the cases, most of them with a positive direction. Subsequently, though with lesser intensity, are the moderate negative correlations. As for the weak correlations, only 4 were identified with a positive direction and 3 with a negative direction. There are only five strong correlations in the positive direction and none in the negative direction.

Table 9 shows the Spearman correlation indices, with a positive direction, for different pairs of individuals. As in the previous study, the table displays a sample of ten records, ordered by correlation index. The first five rows show the initial records, while the last five present the final records.

In the context of strong correlations, the pair formed by individuals 28 and 50 stands out, presenting a high correlation index ($\rho_s = 0.90$, $p = 0.00$). Figure 12 illustrates the calculated index for the neutral facial expression of these individuals during exposure to the stimulus. It is observed that, for

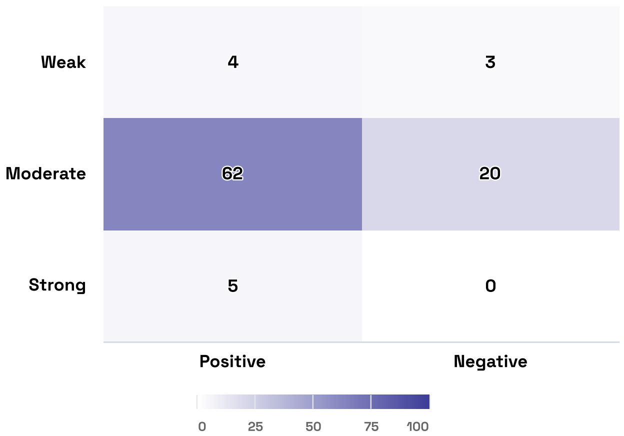

Figure 11. Categorização dos índices de correlação quanto à força e direção, calculados para as reações ao estímulo de surpresa

Individual	Neighbor	ρ_s	p
50	28	0.90	0.00
49	28	0.78	0.00
24	32	0.77	0.00
49	50	0.77	0.00
56	28	0.71	0.00
50	53	0.30	0.03
37	42	0.29	0.04
53	64	0.29	0.04
37	40	0.29	0.04
41	62	0.29	0.04

Table 9. Correlation indices between user pairs for the surprise stimulus.

the majority of the time, they did not display emotions, with the neutral facial expression predominating. Another highlighted case, represented by Figure 13, involves the pair of individuals 29 and 51 who, in addition to presenting a moderate correlation, exhibited variations in facial expressions while watching the stimulus, unlike the pair previously presented. As evidence of contrasting situations, Figure 14 shows a comparison between the neutral facial expression indices for the pair of individuals represented by numbers 29 and 47, who present an inverse correlation.

6.3 Comparison between approaches

In response to QP3, Table 10 presents the data related to the distance obtained from kNN (used for analyzing emotional experience) and correlation (used for analyzing emotional trajectory). For sample representation, the following were selected: i) the first five records with positive direction correlation, ordered in descending order by the correlation index and in ascending order by distance; ii) the first five records with negative direction correlation, ordered in descending order by the correlation index and in ascending order by distance.

The analysis of Table 10 allows us to identify pairs of individuals with similarity both in their emotional experience and emotional trajectory, as well as pairs with differences in both cases. As a key example of mutual similarity, we can cite the pair consisting of individuals identified by numbers 28 and

Individual	Neighbor	ρ_s	p	Distance
50	28	0.90	0.00	0.06
49	28	0.78	0.00	0.04
49	50	0.77	0.00	0.04
24	32	0.77	0.00	0.10
56	28	0.71	0.00	0.14
58	63	-0.70	0.00	1.18
47	29	-0.69	0.00	1.09
51	53	-0.64	0.00	0.81
40	51	-0.50	0.00	0.91
53	57	-0.47	0.00	0.11

Table 10. Correlation indices and distance between individual pairs, considering the AEE and ATE approaches, for the surprise stimulus.

50, who showed a strong correlation ($\rho_s = 0.90$, $p = 0.00$) and small distance (0.06), as discussed earlier. Another interesting case to observe is that of users 28 and 56, who also show a strong correlation ($\rho_s = 0.71$, $p = 0.00$), but with a slightly higher distance than the previous pair (0.14). In this case, it is noted that the difference primarily occurs at the end of the stimulus, where facial expression manifestation occurs at different intensities. In addition to the trajectory representation in Figure 15, Table 11 facilitates the analysis of the average detected facial expressions.

As evidence of individuals who exhibited distinct behavior in the analyses of both approaches, we can cite the pair consisting of individuals identified by numbers 58 and 63. With a strong negative correlation ($\rho_s = -0.70$, $p = 0.0$), these individuals naturally show a higher distance index, as individual 63 maintained a neutral facial expression throughout the entire stimulus, while individual number 58 showed facial expressions associated with emotions, as revealed in Figure 16 and Table 11.

Individual	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	μ_7
28	0.94	0	0.02	0	0	0.02	0.02
56	0.86	0	0.13	0	0	0	0
58	0.09	0.01	0.77	0	0	0.12	0
63	0.99	0.00	0.01	0	0	0	0

Table 11. Comparison of feature vectors of two pairs of individuals from the joint analysis of EAA and ETA.

7 Discussions, Challenges, and Opportunities

As highlighted earlier, this study addresses a topic that has been minimally explored in the literature. Therefore, its methods and results foster discussions that could contribute to the development of new investigations and encourage discussions regarding the use of emotional data in the process of evaluating Human-Computer Interaction quality. In this section, we will present the key points we consider relevant from the results of this research and our perspective on the topic.

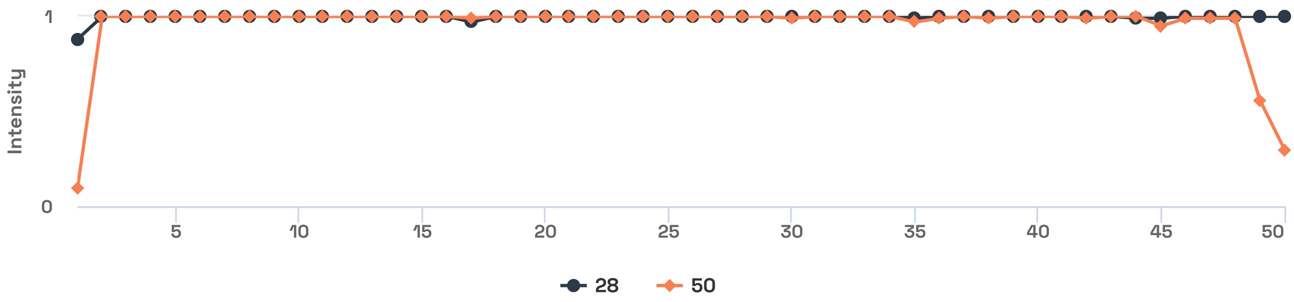

Figure 12. Comparison of facial expression indicators for individuals 50 and 28, showing a high correlation ($\rho_s = 0.90$, $p = 0.00$) for the surprise stimulus.

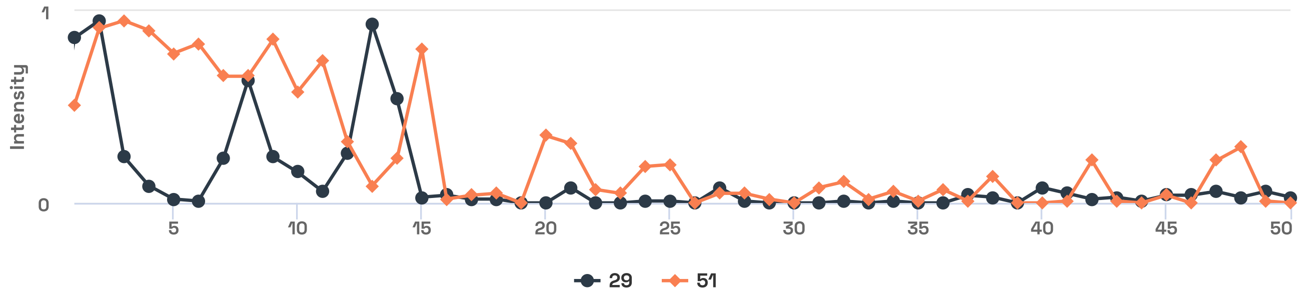

Figure 13. Comparison of facial expression indicators for individuals 51 and 29, showing moderate correlation ($\rho_s = 0.39$, $p = 0.01$) for the surprise stimulus.

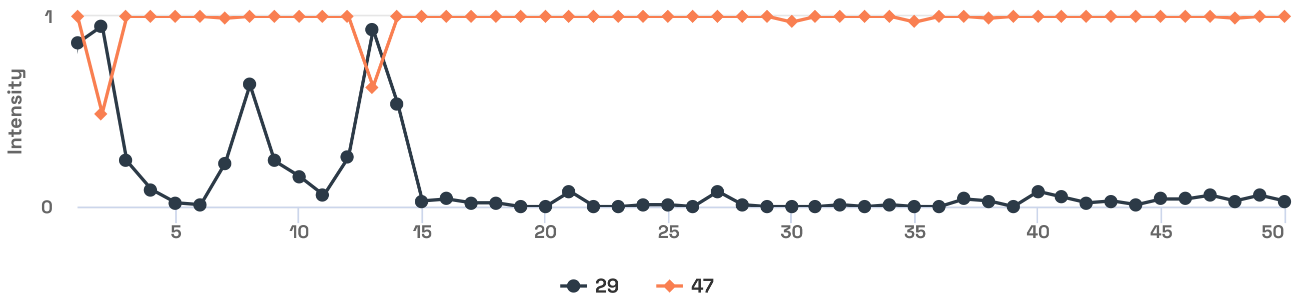

Figure 14. Comparison of facial expression indicators for individuals 38 and 29, showing moderate and negative correlation ($\rho_s = -0.69$, $p = 0.00$) for the surprise stimulus.

7.1 Contributions of the Study

The results presented in Sections 5 and 6 lead to the conclusion that the EEA and ETA approaches are, in fact, effective for comparing the similarity of emotional responses evoked by different individuals from the same audiovisual stimulus, both regarding emotional experiences and trajectories. The results also validate the particularities of the approaches, highlighting that they offer different perspectives for understanding individuals' emotional responses and, therefore, should be chosen through a careful analysis process by researchers concerning the study's objectives. While EEA provides a perspective on the emotions experienced, along with their respective intensities, ETA highlights the emotional changes that occur throughout the stimulus. These approaches can even be combined to identify complete similarity between two individuals. They can also reveal completely opposite behaviors, denoted by a representative index of great distance (EEA) and inverse correlation (ETA). The classification of practices reported in the literature into two approaches, followed by their validation in two studies, not only offers new perspectives for emotional analysis in the context of interactive systems but also opens the way for the exploration of a set of practical applications.

While IS-RSA, as used by Hu *et al*. [2022], is effective in revealing neural correlates of emotional profile similarity, it relies on self-reported ratings and EEG data, which limit its applicability in real-time or large-scale scenarios. In contrast, the EEA and ETA approaches proposed in this work are designed to operate on automatically captured facial expression data, enabling practical, scalable comparisons of users' emotional reactions. EEA offers a global summary of emotional intensity across stimuli, whereas ETA captures temporal variations and the dynamics of emotional engagement. Together, these methods provide complementary perspectives on how individuals emotionally respond to the same content, facilitating applications in affective computing systems without the need for invasive or resource-intensive setups.

Among the contributions, it is important to mention that this work used the Emognition dataset due to its presented characteristics. However, investigations using this dataset typically aim to compare the performance of emotion recognition algorithms, not as a database for comparing emotional responses of different individuals, as was the case in this study. The research by Agung *et al*. [2024], for example, pro-

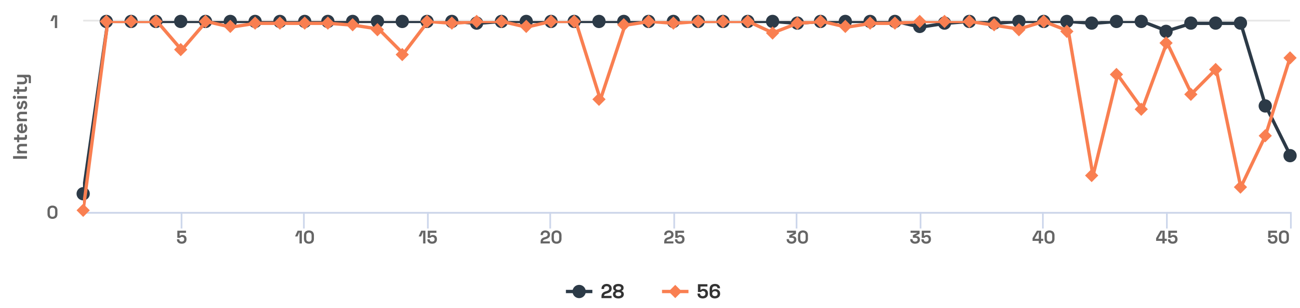

Figure 15. Comparison of facial expression indicators for individuals 28 and 56, showing strong and positive correlation ($\rho_s = 0.71$, $p = 0.00$) for the surprise stimulus.

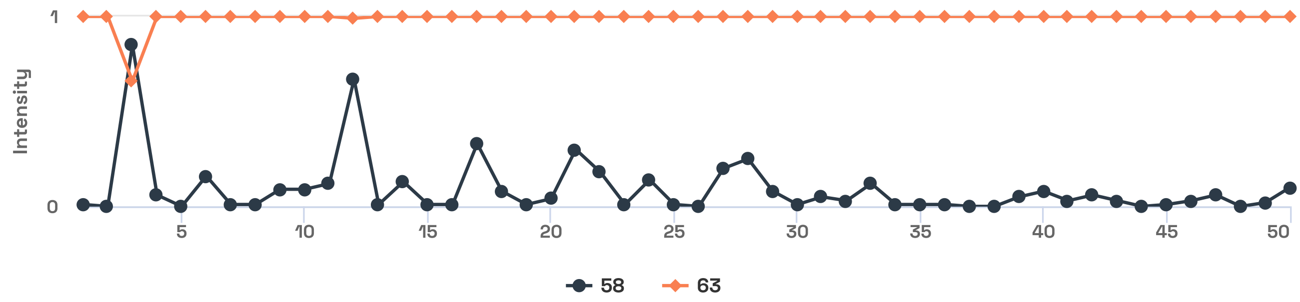

Figure 16. Comparison of facial expression indicators for individuals 58 and 63, showing strong and negative correlation ($\rho_s = -0.70$, $p = 0.00$) for the surprise stimulus.

poses different AI techniques to explore potential improvements in performance and accuracy.

7.1.1 Potential Applications

The proposed approaches can be applied in various real-world scenarios involving affective user interaction. In educational platforms, comparing emotional responses may help identify students experiencing difficulties or disengagement, allowing for adaptive interventions. In entertainment systems, emotional convergence across users can indicate content effectiveness. In healthcare and well-being monitoring, detecting atypical emotional trajectories may support mental health assessment tools. The EEA and ETA methods, being algorithm-independent, are also suitable for integration with multimodal emotion analysis systems combining facial, physiological, and behavioral data.

7.2 Datasets

Conducting a study such as this inevitably requires the collection of emotional responses from different individuals to the same emotional stimulus. However, this task is inherently complex. In addition to recruiting volunteers, who must authorize the use of their images in scientific research, it is necessary to organize a set of stimuli capable of generating emotional responses in the individuals who observe them. The choice of stimuli involves a risk to consider: the stimulus will not always be capable of evoking emotions in people and may provoke emotional responses distinct from those anticipated by the researchers.

Additionally, participants in the data collection process may feel that they are being observed, monitored, or judged and, for this reason, may engage in self-censorship in certain situations. In the case of this dataset, for instance, participants were in a controlled environment, also using physiological sensors, which could certainly influence their emotional responses. At this point, the participants' fatigue must also be considered. In the current dataset, the videos displayed were of short duration, but the volunteers were exposed to multiple stimuli. Over time, contextual factors, such as physical fatigue, may influence emotional responses to the presented content.

Another essential aspect for conducting studies of this nature is the possibility of comparing the emotional responses of different individuals. As explored at the beginning of this paper, few datasets enable synchronization of data collected from different users. Often, datasets contain facial expressions generated by actors or, when collected spontaneously, lack resources to identify when two individuals reacted to a particular event in the same video, for example.

7.3 Human Factors

The two approaches presented in this study allow for analyzing the similarity of emotional responses between different individuals, but there is room to explore why some individuals react similarly while others do not. The literature reveals that, in recent years, there has been an increasing interest from both the scientific community and the industry in developing adaptable computational applications, capable of offering resources and tools aimed at providing better user experiences as well as supporting learning and training processes. In these contexts, understanding the factors that influence human emotional responses can enrich the development process of these applications, making them more effective in their goals.

In this sense, it is promising to include characteristics associated with human factors in the analysis, such as demographic data, personality traits, or temperaments. Several studies explore the relationships between such human aspects and emotional responses, though not always in detail that would enable the scientific community to discuss these relationships and specifically prospect interventions or strategies best suited for each user profile. The challenges here are often related to sampling issues. To obtain statistically significant data, a large number of participants and experiments may be required, as there is no uniformity in the population distribution when considering demographic factors, such as personality traits.

Also, the importance of cultural factors in the expression of emotions through facial expressions must be considered. Studies indicate that culture strongly influences how emotions are expressed, resulting in significant variations in facial and gestural patterns. This cultural diversity highlights the need to observe these cultural and regional particularities to obtain a more accurate analysis for each context. Given the cultural homogeneity of the dataset, future research should aim to explore emotional responses from more diverse populations, particularly from underrepresented regions such as Latin America and Africa, to identify potential cross-cultural differences in facial expressiveness.

7.4 Extrapolation to User Experience Evaluation

As explained throughout this document, one of the motivations for this work is to obtain information that can not only stimulate discussions in the field of Affective Computing but also contribute to the use of emotional responses for evaluating user experience. In this regard, two important aspects must be considered: the evaluation of systems in which there are synchronous events and the evaluation of applications in which there are asynchronous events.

Throughout this study, approaches were discussed regarding the comparison of responses to emotional stimuli from audiovisual content, whose events can be synchronized, even if the individuals did not interact with the content at the same time. In interactive applications, however, the process presents other challenges, as each user may experience different paths during the use of the application. Thus, promoting associations between the emotional responses of different individuals may require specific approaches that consider this diversity of events.

Another relevant aspect to consider is the inclusion of other data obtained through other emotion recognition techniques for detecting similarities. In addition to facial expressions, data collected through electroencephalography, for instance, could contribute to a better understanding of the emotional impacts triggered by a particular stimulus. However, joint analysis involves certain challenges, such as the need to adopt some strategy for multimodal fusion. One must also consider how to represent this set of information in a way that is understandable, since each technique generates a significant amount of data.

8 Threats to validity

This study presents relevant insights into the comparison of emotional responses to audiovisual stimuli, yet some limitations and potential threats to validity must be acknowledged.

External Validity. The generalizability of our findings is constrained by the characteristics of the dataset used. Although the Emognition dataset includes synchronized emotional responses from multiple participants, it comprises only Polish-speaking individuals aged between 19 and 29. Cultural and demographic homogeneity may limit the applicability of our conclusions to broader populations. Future work should explore datasets from more diverse cultural and demographic contexts to investigate cross-cultural variability in emotional expression and response.

Construct Validity. Our study does not focus on evaluating or comparing emotion recognition algorithms per se. Rather, it assumes the output of a widely used tool (Face-api.js) as input for further analysis. While this decision ensures consistency across all samples, we recognize that biases inherent in the algorithm or its underlying training data may affect the accuracy of the emotion labels. Importantly, the two approaches we propose (EEA and ETA) are independent of the specific recognition tool employed and can be applied to data from various sources. Nonetheless, more discussion on algorithmic fairness, especially regarding race and cultural bias, remains necessary and is identified as a direction for future research.

Internal Validity. The processing steps adopted (e.g., frame sampling at 1-second intervals, exclusive analysis of disgust and surprise stimuli) were designed to reduce computational complexity and scope. However, such decisions may overlook subtle emotional variations or temporal nuances. The mutual exclusivity constraint of the facial expressions recognized by *Face-api.js* may also limit the ability to capture mixed or transitional emotions.

Ethical Considerations. The study used a publicly available dataset collected with informed consent and ethical approval from the Wroclaw Medical University (Approval no. 149/2020). Participants agreed to have their data processed and shared for research purposes. In compliance with Brazilian regulations (CNS Resolutions 510/2016 and 674/2022), no additional ethical review was required for this secondary analysis. No identifiable images were reproduced, and all data were handled in accordance with usage terms and privacy guidelines. Still, the broader ethical implications of using facial expression data—including the risks of misuse or misinterpretation—should be discussed more explicitly in future research.

Reproducibility. In line with Open Science practices, we provide access to the preprocessed dataset used in our analysis. While some preprocessing scripts and analysis codes (e.g., for kNN and Spearman correlation) are not yet publicly available, we plan to make them accessible in future updates to enhance reproducibility and transparency.

9 Final remarks

The constant technological transformations and the increasing adoption of computational resources as tools for entertainment and support in training, rehabilitation, and learning processes have increasingly demanded solutions that combine technical quality with a good experience for users. In this context, the real-time recognition of users' emotions has shown promise both for evaluating user experience and for defining potential adaptations to be made in these applications. However, the challenges do not stop at data collection. Understanding emotional data and attributing meaning to them is a complex, interdisciplinary issue and crucial for advancing investigations in the field of Affective Computing.

Seeking to contribute to the discussions in this regard, this work explored two approaches to comparing emotional responses from different individuals to two videos that aimed to evoke disgust and surprise emotions in their viewers. In both cases, we observed that the approaches were effective in their objectives. The emotional experience analysis allows us to identify individuals who, during the stimulus, displayed facial expressions with similar intensities, regardless of the moment in which they occurred. On the other hand, the emotional trajectory analysis is capable of indicating that two individuals expressed emotions on their faces in a similar temporal trajectory.

Although the results of this work are not definitive, they provide the foundation for further discussions and investigations that seek to deepen the understanding of the emotional influence of stimuli on individuals who, despite having distinct characteristics, may react similarly to certain content. Advancements in this understanding could provide significant contributions to the development of adaptive computational applications, as well as to the evaluation of user experience in non-traditional contexts. Throughout this work, limitations, challenges, and opportunities for contribution were presented, raising new investigations by the scientific community, such as the need to conduct studies involving other samples, the analysis of demographic, cultural, and personality data. Building upon the challenges and opportunities outlined in this study, there is a clear need for interdisciplinary collaboration, particularly between the fields of Computing and Psychology. Such collaboration would aim to address ethical considerations, promote transparency, and advance the principles of interpretability and explainability, ultimately contributing to the design and quality of intelligent systems that are both effective and responsible.

Declarations

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Authors' Contributions

GOA and JPDE contributed to the data curation and programming. THN, CXPJ, LVMCC and RVA contributed to the conceptualization and writing of the paper. GOA, JPDE and RVA performed the experiments. All authors read and approved the final manuscript.

Competing interests

The authors declare they have the following competing interests.

Availability of data and materials

The raw data used in the analysis is presented at `https://github.com/medialabufmt/emotion-jis`. The dataset used (Emognition) is publicly available under a scientific use license[4].

Citation Diversity Statement

During the preparation of this work, we sought references strictly related to the topics addressed, consulting scientific databases in English and Portuguese. The references were selected exclusively for their relevance and contributions to the research, without any omissions due to bias.

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