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Modelling and statistical analysis of emotions in 3D space

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Abstract

Emotional Intelligence provides an impetus for simulating human emotions in systems to make emotionally-sensitive machines. Integrating emotion-based theories and principles maturing with research in affective computing, we propose a novel statistical approach that can evaluate the correlation between different emotional states. It provides a way specialists can address the development of the entire passion experience, as reviewed through self-report. We also represent a three-dimensional model that can accommodate affect variabilities and analyze the distribution of affective states in valence, arousal, and dominance. The main idea is that human emotions can be quantified by measuring their degree of emotions. To the best of our knowledge, this is the first step in this direction, and we have proposed and successfully implemented it to induce feelings in robots and games.

1. Introduction

Emotion plays a significant part in interpersonal communications. A complex cognitive state is liable to have a recognizable and definite cause. Affective computing, also called Emotion artificial Intelligence, is an arising innovation that empowers computers and machines to classify, measure, and simulate human sentiments. It is an interdisciplinary field spreading over software engineering, brain research, and intellectual science. This area also fascinated many experts from various domains to study biological measures and execute them in different applications. Automatic recognition of emotions helps to understand the feelings of people who can't express their thoughts, like mature people, little kids, and people with mental disabilities. It may be utilized in predicting stress among people doing stressful tasks. It may be carried out in a robot to catch an individual's feelings and act as per their state of mind. There are earlier works revealed in literature for emotion recognition from various modalities, such speech prosody [1], gestures [2, 3], facial expressions [4]. However, these modalities are not suitable for perceiving the emotion of people with severe mental disabilities or little kids since they can't communicate it appropriately. Most researchers use behavioral responses and physiological signals generated by these modalities to understand emotions more appropriately [5]. Researchers have moved toward recognizing emotions from one of two essential perspectives: (1) the discrete/basic emotions (2) that emotions can be portrayed on a dimensional premise in groupings. Emotion-based theories were proposed by Charles Darwin [6] and William James [7] in the nineteenth century. As per Picard [8], feeling plays a massive part in perception, learning and decision making. Ekman [9] proposed six discrete emotions: disgust, happiness, fear, sadness, anger, and surprise. Parrot [10] proposed an emotion tree-like structure. Additionally, a dimensional model has been proposed from the discrete emotions model. Wilhelm Max Wundt [11] described emotions by three dimensions: 'pleasurable versus unpleasurable', 'strain or relaxation' and 'arousing or subduing'. After that, Emotion wheel by Plutchik [12] and valence-arousal model by Russell [13] became popular among dimensional models of emotions. Here and there, a third dimension called dominance is likewise consolidated in this model; however, the valence-arousal model mostly catches subjective parts of feeling. Usually, valence ranges from positive to negative and portrays loveliness or disagreeableness. Arousal ranges from low to high and tells about the actuation. Dominance communicates the level of control created by the stimuli.

Over the most recent couple of years, the more significant part of the research depended on posed and spontaneous data obtained in a research center for affect detection. However, researchers have revealed various complex affective states like depression, thinking, embarrassment, etc, that have been used in everyday communication. Some researchers showed that cognitive mental conditions such as agreement, disagreement, unsure, etc, happen more frequently in daily interactions than the alleged essential or primary affective states. These cognitive states were tracked down as pertinent to portrayal for affection recognition (e.g., [1]). Such complex and non-basic affective states can be exhibited via anatomically possible facial expressions, body gestures, and physiological signals. Accordingly, a single label or any modest number of discrete classes may not mirror the intricacy of the emotional state carried by such rich wellsprings of data [13]. Recently, various researchers advocate the utilization of dimensional depiction of human emotions, where emotions are not autonomous; instead, they are gradually related to each other (e.g., [14, 15]). They began investigating the dimensional model of emotions to catch activity units (AUs) viably. Two- or three-dimensions emotion primitives can classify the subtle and complicated affective states. Therefore, this work represents the 3D model that can accommodate affect variabilities and analyze the distribution of affective states in terms of valence, arousal, and dominance. Further, a unique approach is proposed to predict the correlation and measure the distinct affective states.

1.1. Motivation

- The capacity to provide machines with emotional intelligence, particularly the ability to simulate empathy, is one of the motives for the study.
- Emotion artificial Intelligence is the future and facilitates human capacity to manage complex emotions like depression, stress, anger etc.

1.2. Aim and significance

The current study carries further information about the emerging field of multidimensional research within the cognitive psychology of emotions. We have examined and explored the research work on representing emotions in 2D space. The objective of this study was not to address how many dimensional characteristics emotion space has but to look at the utilization of the proposed model working with multiple dimensions in the examination of the general design of the semantic space for affective states. More specifically, we utilized three distinctive emotion primitives: valence, arousal, and dominance as input information for this model. We predicted that every one of the three input dimensional estimators would be correlated and generated an emotion wheel for determining its vital improvement in emotion recognition performance. Accordingly, the actual output of the current investigation is the development of the emotion wheel based on the Euclidean angle, including the locations of the primary emotion samples as the essential constitutive components of semantic feeling space. Therefore, we presented an innovative insightful methodology to analyze emotions apart from the traditional, two-dimensional pattern.

The essential contribution of our work is as follows:

- We propose a unique model to quantify various emotions through the emotion wheel. To the best of our knowledge, this is the first step toward this direction instead of using any machine learning algorithms.
- The model is efficient in analysing the distribution of various emotions in three-dimensional space. A significant correlation is established between the emotions and the participant's ratings.
- We have proposed and successfully implemented it in order to enhance the learning process in games. The proposed model has the advantage of estimating the degree of comparison between various affective states.
- We employed the multimodal datasets DEAP [16] and DREAMER [17], which have various affective states to test our proposed model, and test results to validate our model's efficiency and robustness.

There are six sections overall in this paper. The impact of different emotions during clustering in VAD space is shown in the third section. The DEAP and DREAMER, multimodal emotion databases, and results are discussed in the experimentations and analysis section. The overall technical analysis is discussed in the fifth section. At last, we concluded the work in the last section.

2. Related work

In literature, the researchers categorize emotions in three emotion models, namely (i) the categorical model, (ii) the dimensional model, and (iii) the appraisal-based model. According to H Gunes *et al* [18], the categorical model deals with a primary and small number of emotions that can be recognized universally. Ekman *et al* [19] recognize six discrete emotions: happiness, sadness, anger, surprise, fear, and disgust, which can be recognized universally. In the categorical model, compound feelings cannot be interpreted enough into a restricted arrangement of words. A few analysts attempted to characterize numerous mixed emotion classes (e.g., sadly, surprised, fearful, happily) [20]. In a dimensional model, the affective states are related to each other orderly, and emotional variability is mainly represented by three emotion primitives: valence, arousal, and dominance (VAD). Suppose the affective states are more complex and cannot be characterized by a single level. In that case, we can use the dimensional model of emotion to measure the intensity of every affective state on a continuous scale. Few studies [20] have reported a 4D model with one more emotion primitive, i.e., relevance. In an appraisal-based model, we deal with emotions generated through continuous evaluation of the outside world's internal state and external state [18].

The major drawbacks of the categorical approach to emotion recognition can be summarized as:

- Discrete emotions cannot define a large number of emotions that arise in daily communication settings. They are just limited to only 6–8 affective states.
- The intensity of emotions cannot be measured in the categorical approach as intense emotions are bound to induce some unusual behaviour in human beings.
- Moreover, the categorical approach for emotion recognition does not signify a dimensional emotion space and has no algebra: every emotion must be studied and recognized independently.

2.1. Affect representation in 2D and 3D

Emotion classification is an apex module to deal with the variability in the human affective states in emotion classification. A continuous-valued scale is one way to categorize as it can define the power of affective states [19]. In a multidimensional approach to emotion modeling, the effect variability is represented by n dimensions, generally 2D or 3D. In the 2D model, valence and arousal are the most used emotion primitives that characterize emotions from activation/non-activation and the positive/negative affective state. Whissell [21] designed the 'dictionary of affect' in language with scores to quantify the Activation and Evaluation dimensions to measure emotions. They have represented the specific position of each emotive word in the emotional space, as shown in figure 1. The emotional space consists of two dimensions: Activation (x) and Evaluation (y). Emotions (sample of 54/107 words) annotating the constructed circle were taken from Whissell's dictionary itself. The mapping of emotions is carried out by considering the z- score of each emotive word. It is worth noting that the emotions 'serene' and 'calm' lie in different quadrants, whereas they should lie in the same quadrant.

Furthermore, emotions' happy' and 'surprise' lie in the same quadrant I. In addition, it is difficult to analyze complex emotions correctly from Whissell's emotional space like 'greedy' and 'guilty' emotions. Therefore, it can be observed that the two-dimensional model is not a reliable model or approach to measuring emotions. Here comes the need for one more dimension to measure emotions accurately. The most common three-dimensional space is Valence, Arousal, and Dominance (VAD). However, little literature [22] used Pleasure as one dimension in place of valence. S Kolestra *et al* [16] included one more emotion primitive: liking for emotion recognition. An affective state can be depicted freely by the three primitives (VAD) measured on a continuous-valued scale. The 'valence' ranges from unpleasant (say sad) to pleasant emotions (say happy), whereas 'arousal' ranges from sleeping to frantic excitement, and 'dominance' refers to the degree of intensity of emotions (how strong the emotion is) [23]. Other measures are liking and familiarity (given in the DEAP dataset). Liking measures inquiries about the participant's perceptions, not their feelings.

The related research fields of emotion classification have achieved remarkable results. Researchers generally tried to extract the best features and classify emotional states through many algorithms. Wang and Cheong *et al* [24] introduced multimodal emotion recognition based on probabilistic inference. The features are obtained from psychology and cinematography rules. They used a support vector machine to classify 36 full-length movies data divided into 2040 scenes.

S Arifin *et al* [22] proposed a system for automatically extracting emotion from videos. They used an affective video content analysis model based on a hierarchical dynamic Bayesian network (HDBN) to retrieve affective level information. Then a spectral clustering algorithm was applied to determine the emotional segments of the video. They considered pleasure-arousal-dominance (PAD) dimensions for affect representation. The

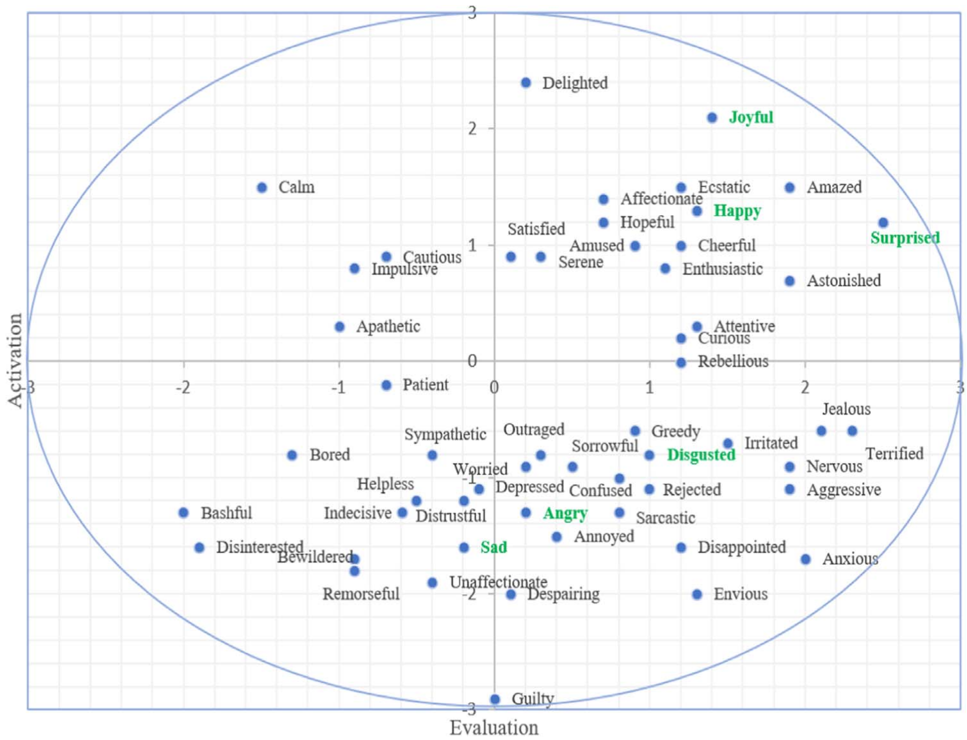

Figure 1. Whissell's two-dimensional space.

performance of the system was compared with the time adaptive clustering algorithm. They used six emotion categories with one emotion per video, a total of 10790 shots and 762 video segments extracted from 43 videos.

Zhang *et al* [20] proposed an approach uniting support vector regression (SVR) and affective psychological model to attain modified affective analysis. They used MTV video to develop a personalized affective model based on the computation of arousal with a linear combination of arousal and valence features. Soleymani M *et al* [25] built connections between audio-visual, physiological, and self-appraisal of valence-arousal. They utilized a dataset of 64 film scenes extricated from 8 Hollywood motion pictures. Later, they proposed a Bayesian framework for affective video representation using audio-visual features.

G Irie *et al*'s [26] work is twofold: (1) they proposed a strategy to retrieve emotion class-specific audio-visual features, named Affective Audio-visual Words (AAVWs). It is used to disengage highlights that are unequivocally identified with the watcher's feelings. (2) They proposed a clustering prototype named Latent Topic Driving Model (LTDM) to delineate extracted features to the emotion classes. They experimented on 206 film scenes separated from 24 movie titles of 8 emotion classes given by 16 subjects.

N Malandrakis *et al* [27] proposed a supervised learning method to model the continuous affective reaction using hidden Markov Models (HMM). The model is designed to classify video frames into one of seven distinct classes, and then these discrete-valued curves are changed to constant values via spline interpolation. They used 30-minute movie clips for experimentation.

L Yan *et al* [28] proposed a content-based algorithm for affective content recognition of the video by integrating unascertained theory and clustering. They have considered brightness, shot cut-rate, and color efficacy in a video scene as low-level features. They built an unascertained clustering model of video, then applied a method to specify the index weight of each emotion feature and performed video clustering. They used 112 video scenes segmented from four films.

L Canini *et al* [29] proposed an affective framework for the affective description of movies through their connotative properties. According to Canini, connotation gives a middle-of-the-road portrayal that adventures the objectivity of varying media descriptors to foresee the subjective enthusiastic response of the user. They build up the connection between audio-visual features and connotative rates. An overview of affective computing in terms of mode, stimulus, features extracted, target factors and the domain is given in table 1. However, most existing affective analysis studies focus on removing features through machine/deep learning algorithms and achieving better emotion recognition results. Instead of using these algorithms, we proposed a comparative approach to compute the set of distinct emotions. We develop the emotion wheel based on the Euclidean angle, including the locations of the primary emotion samples as the essential constitutive components of semantic feeling space.

Table 1. An overview of affective computing in mode, stimulus, features extracted, target factors, and domain.

			Mode					
System	Year	Stimulus	Uni-modal	Multi-modal	Features	Classifier	Target Factors	Applications
[30]	2021	IEMOCAP and EMODB	No	Yes	Spectrogram and statistical features	Autoencoder	Seven Emotional states	Speech Emotion Recognition (SER)
[31]	2021	CGnA10766	Yes	No	Low-Level and Abstracted features	Convolutional Neural Network (CNN)	Valence and Arousal	Image Emotion Recognition
[32]	2020	Own database	Yes	No	Time domain, Frequency domain ECG features, Non- Linear Analysis	Least-squares support vector machine (LS-SVM)	Valence, Arousal, and four affective states	Listening to music
[33]	2018	AMIGOS	No	Yes	Statistical, Non-Linear, Time domain, frequency domain features	Deep-CNN	Arousal and valence	Affective Recognition
[34]	2020	DREAMER and AMIGOS	No	Yes	Statistical features, wavelet features, and temporal features	2D-CNN, 1-D CNN, and Long Short-Term Memory (LSTM)	Valence and arousal	Human–Computer Interaction (HCI)
[35]	2020	DEAP	Yes	No	PSD and valence features.	Deep Neural Network	Positive and negative valence	Neuromarketing
[36]	2021	Native Chinese emotional clips	Yes	No	Power spectral density (PSD) and Differential Entropy (DE) features	SVM	Positive and negative	Disorder of consciousness
[37]	2020	Database from PhysioBank	No	Yes	heart rate variability features, power, and entropy features	SVM, K-nearest Neighbor, and Decision Tree	Cognitive load	Pattern Recognition
[38]	2019	AMIGOS	Yes	No	Time domain, frequency domain, and time-frequency domain features	SVM-Radial Basis Function	Valence and arousal	Human-Machine Interaction

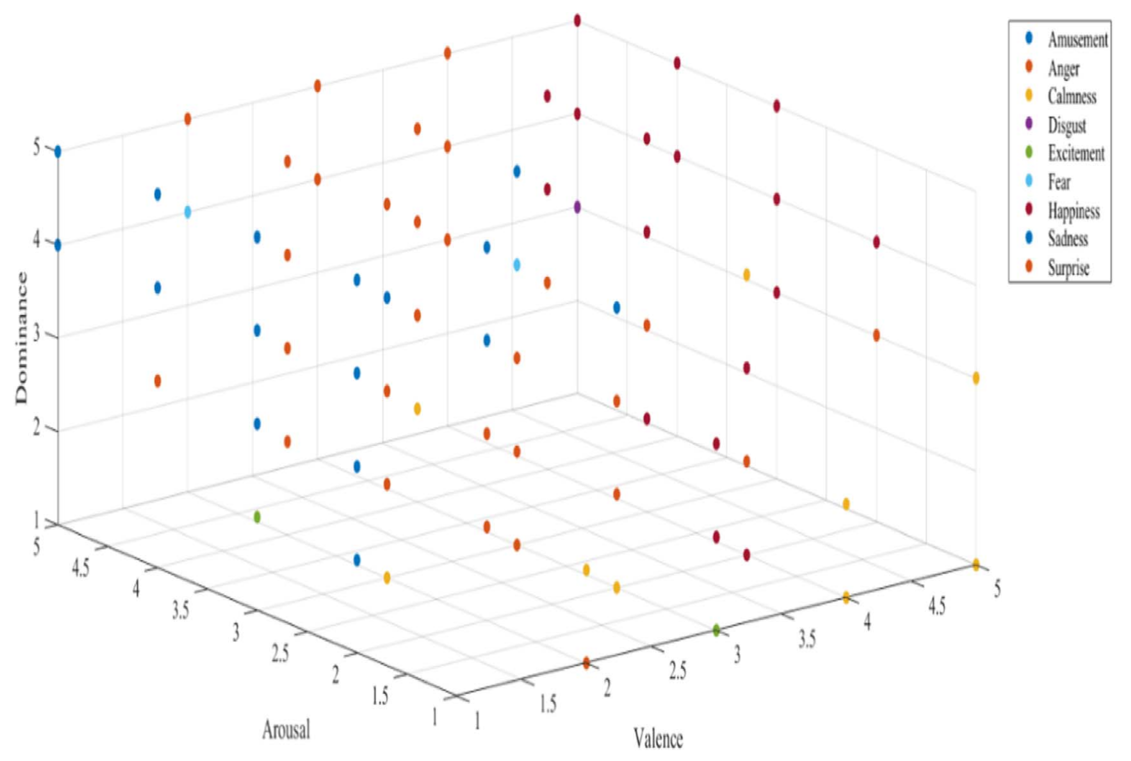

Figure 2. Distribution of DREAMER's emotions in 3D space.

3. Methodology

We represent a three-dimensional model that can accommodate affect variabilities and analyze the distribution of affective states in terms of valence, arousal, and dominance. The model's versatility has been explored on two notable datasets—DEAP and DREAMER, which depict spontaneous emotions in unmistakable and dimensional spaces separately. There is no earlier information about their relative areas in three-dimensional VAD space. So, it is essential to build up the area in VAD space where every emotion can be viewed as effectively located and their general positions and distances. For this reason, every instance of each emotion (given in datasets) was placed in the VAD coordinate system. The data was then analyzed to see any anomalies or inconsistencies.

3.1. Emotion representation in VAD space

We have plotted all 414 values (as shown in figure 2) and 1280 values of distinct emotions (as shown in figure 3) respectively from DREAMER and DEAP databases in three-dimensional space to validate the proposed model. Each complex emotion inhabits a position in this space. All the VAD values are the subjective assessments of each participant taken on a continuous scale in the range of 1–5 and 1–9 that were used as the ground truth data of DREAMER and DEAP databases, respectively. After collecting the VAD values for each emotion, the data was analyzed to perceive any irregularities or inexplicable discrepancies. To attain the degree of continuous dispersion of emotions in VAD space, the relative standard deviation (RSD) or the coefficient of variation was computed. RSD is a common method to measure variability in data, and it is defined as the ratio of the standard deviation (SD) to the estimate. The zero value of RSD signifies no affect variability, while the high RSD value signifies more affect variability in 3D space. The mean RSD for all emotions in DEAP was 0.33 ± 0.1 for valence, 0.40 ± 0.1 for arousal, and 0.39 ± 0.08 for dominance, representing affect variability across VAD values.

Furthermore, the average SD for valence, arousal, and dominance were 1.59, 1.83, and 1.82, respectively, which shows variation in various instances of a particular emotion. Similarly, the average RSD and SD values were calculated for each emotion in DREAMER on three continuous dimensions to attain affect variability in the database. The mean and SD values for various affective states of DREAMER and DEAP are given in tables 2 and 3, respectively.

As evident from figures 2, 3 and the average RSD, SD values, it can be seen that all affective states are continuously distributed in the VAD emotion space. In any case, it is clear that such a significant and consistent spread of each emotion cannot be just because of a noisy experiment. Any emotion (say Sad) can have diverse Valence, Arousal, and Dominance estimators, relying upon various incitement impacts. Consequently, at

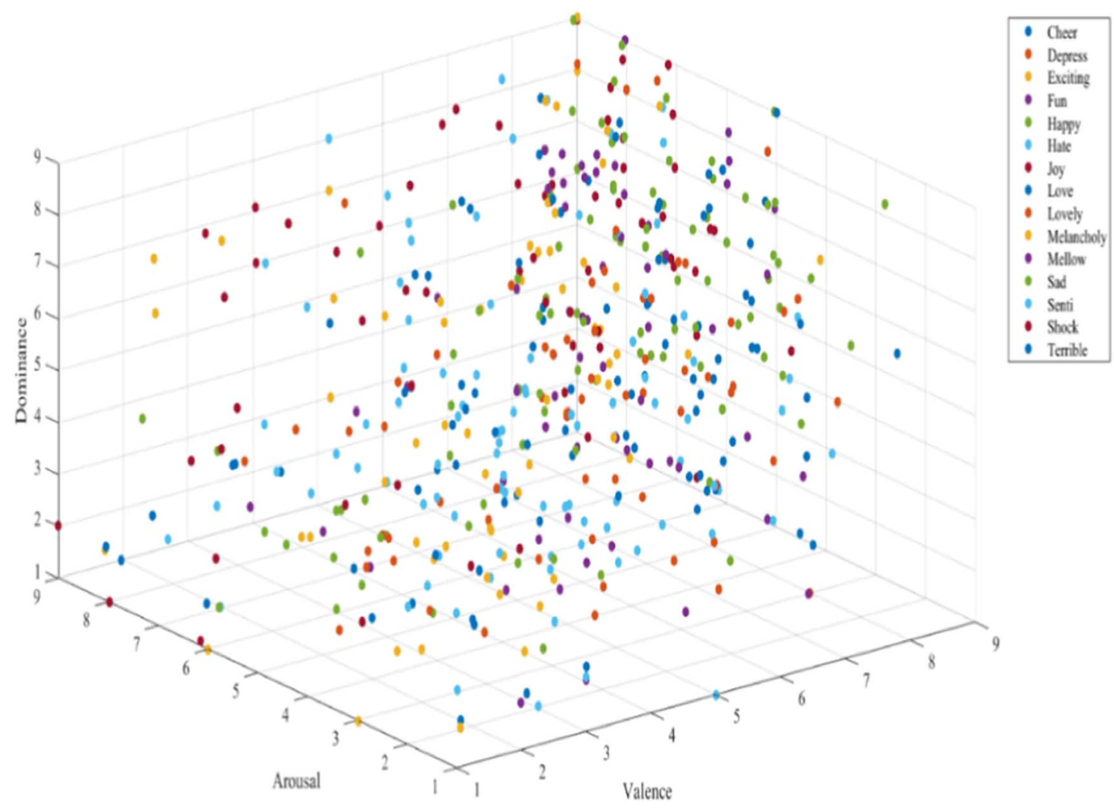

Figure 3. Distribution of DEAP's emotions in 3D space.

Table 2. Mean and SD ratings of target emotions on three dimensions in the DREAMER database.

Emotions	Valence	Arousal	Dominance
Amusement	4.26 ± 0.71	3.22 ± 1.04	3.26 ± 0.94
Anger	1.85 ± 0.81	3.09 ± 1.18	3.37 ± 1.19
Calmness	3.57 ± 0.77	2.11 ± 0.79	2.35 ± 0.84
Disgust	2.43 ± 1.36	3.57 ± 0.95	3.83 ± 0.94
Excitement	3.43 ± 0.95	3.52 ± 0.9	3.39 ± 1.03
Fear	2.26 ± 0.94	3.67 ± 1.02	3.67 ± 0.98
Happiness	4.46 ± 0.62	3.43 ± 0.99	3.65 ± 0.96
Sadness	1.46 ± 0.62	3 ± 0.91	3.72 ± 0.88
Surprise	2.85 ± 0.83	3.46 ± 1.02	3.13 ± 1.03

different moments, a subject can be sad in one moment and can be sadder (upset) at another moment. Our representation dimensional model can oblige all of these affect variabilities as all three dimensions are continuous. It also provides a promising approach to linking and measuring distinct affective states.

3.2. Modelling of emotion wheel: a relative approach to compute the set of distinct emotions

This section proposed a comparative approach to compute the set of distinct emotions and construct the emotion wheel. After representing emotions in three-dimensional space, we calculated the average angle of each emotion to its origin. This angle defines the shortest angle at which any emotion is rotated about the origin and is responsible for postulating the erection of emotions.

We used VAD values to represent any particular emotion in a three-dimensional system at various instances. We took another reference point (1,1,1) as VAD values lie in the range of 1–5 and 1–9 in respective DREAMER and DEAP databases. Then, each emotion's average angle is computed (consider all instances) to construct the emotion wheel and attain a definite pattern. To maintain normality, we have also taken out a portion of the outliers, the data points with unusual distance from other values in a dataset. The standard formula defines the angle (Θ) between two vectors:

Table 3. Mean and SD ratings of target emotions on three dimensions in the DEAP database.

Emotions	Valence	Arousal	Dominance
Cheerful	6.86 ± 1.3	5.86 ± 2.2	6 ± 1.56
Depressing	5.93 ± 2.05	6.93 ± 1.98	5.5 ± 2.41
Exciting	7.14 ± 1.19	4.86 ± 1.46	5.21 ± 1.32
Fun	6.93 ± 2.32	6.47 ± 1.93	5.8 ± 2.01
Happy	5.93 ± 1.79	3.36 ± 1.34	4.93 ± 1.79
Hate	6.57 ± 1.4	4.21 ± 2.51	5.43 ± 2.06
Joy	6.47 ± 1.36	4 ± 1.79	4.93 ± 1.91
Love	4.2 ± 1.42	3.73 ± 1.81	3.93 ± 1.95
Lovely	3.33 ± 1.19	4.47 ± 2	3.2 ± 1.38
Melancholy	3.33 ± 1.35	2.93 ± 1.69	4.67 ± 2.15
Mellow	4.2 ± 1.64	3.6 ± 1.2	4.6 ± 1.82
Sad	4.2 ± 1.8	3 ± 1.51	3.33 ± 1.78
Sentimental	3.67 ± 1.49	5.47 ± 2.06	4.6 ± 1.74
Shock	4.67 ± 1.49	6.4 ± 1.93	4.93 ± 1.57
Terrible	3.93 ± 2.05	6.13 ± 2.09	5.53 ± 1.89

Algorithm 1. Procedure for constructing the emotion wheel for analyzing human affective states.

Require: Multimodal dataset associated with VAD ratings
Ensure: All affective states are continuously distributed in the VAD emotion space and remove the portion of outliers;
1: Extract all VAD values for each affective state (all instances) from the respective dataset;
2: **repeat**
3: Initialize the vector U for each emotion state;
4: Regularizing another vector V at the minimum value of the dataset;
5: Calculating the scalar product

$$(\mathrm{U, V})_{\mathrm{R}} = \sum\nolimits_{i=1}^{n} U_i V_i; \text{(refer to equation (3.2))}$$

6: Calculating the Euclidean Norms

$$\mathrm{Norm\,[U]} = ||\mathrm{U}||, \mathrm{Norm\,[V]} = ||\mathrm{V}||; \text{(refer to equation (3.3))}$$

7: Calculating the Euclidean angle Θ and form matrix $\mathrm{S}^{\mathrm{m\,n}}$

$$\mathrm{S}^{\mathrm{m\,n}} = \mathrm{real\,(acosd\,((U, V)_R/Norm\,[U]\,{}^{*}\,Norm\,[V])))};$$

8: Transform data within range 0°–360° for constructing emotion wheel;
9: **until** the iterations calculate results for each affective state

$$\cos\Theta\,(\mathrm{U,\ V}) = \frac{Dot\ Product}{Eucledian\ Norm}$$

$$\cos\Theta\,(\mathrm{U,\ V}) = \frac{(U,\ V)_R}{||\mathrm{U}||\ ||\mathrm{V}||}$$

$$\Theta = \mathrm{ArcCos}(\cos(\mathrm{U,\ V})) \tag{3.1}$$

Where $(\mathrm{U, V})_{\mathrm{R}}$ defines scalar product for any pairs of vectors $\mathrm{U, V} \in \mathrm{X_R}$ in any real vector space $\mathrm{X_R}$. The scalar product is defined as:

$$(\mathrm{U,\ V})_{\mathrm{R}} = \sum_{i=1}^{n} U_i V_i\ ; \ \ \text{where } \mathrm{n} \geqslant 2 \tag{3.2}$$

$$\text{and } ||\mathrm{U}|| = \sqrt{(U,\ U)_R}\,;\ ||\mathrm{V}|| = \sqrt{(V,\ V)_R} \tag{3.3}$$

$||\mathrm{U}||$ and $||\mathrm{V}||$ denote Euclidian norm or magnitude of respective vectors U and V.

Then, we have constructed an emotion wheel based on the average Euclidian angle of each emotion to origin for both datasets. The emotion wheel is an illustration that represents a different number of emotions and their relationships among them. The detailed procedures for constructing the emotion wheel for analyzing human affective states are summarized in algorithm 1.

4. Results

4.1. Experiments with DEAP database

In this section, we conduct extensive experiments on the benchmark multimodal physiological database commonly used in emotion recognition to evaluate the effectiveness of the proposed method—DEAP. This dataset comprises of electroencephalogram and other peripheral physiological signals of 32 participants (16 males and 16 females), where every participant watched 40 one-minute-long passages of music videos. Participants appraised their emotional reactions to every video on the scales of valence, arousal, dominance, liking, and familiarity. The front-facing video for 22/32 participants was likewise recorded, and the data was pre-processed, which depicts the emotions in dimensional space. We adopt the same procedure as described in section 3 to examine the versatility of the proposed model for the DEAP dataset.

The angle of each emotion's instance w.r.t origin is calculated, and some sample values are given in table 4. Then, the degree of every emotion (average Euclidian angle) is computed as shown in table 5, and construct the emotion wheel accordingly.

It is worth observing that all areas of the emotion wheel are signified, though with somewhat different densities. As seen from figure 4, similar emotions are adjacent in the wheel, while opposite terms are far from each other. The Outer circle shows the various emotion states with their average angle to the origin, and the inner circle represents the multiple clusters of emotions. The label 'others' in the respective figures represents the possibility of accommodating many other affective states in the wheel. This approach estimates the level of correlation between different affective states. The DEAP emotion wheel is shown in figure 4 This emotion wheel groups 15 affective states in 6 main clusters using K-means clustering. These six clusters are:

C1: Happy, Fun, Exciting, Joy, Lovely (Happy Cluster)
C2: Depress (Depress cluster)
C3: Love, Cheer, Senti (Love cluster)
C4: Melancholy (Melancholy cluster)
C5: Terrible, Hate, Mellow (Hate cluster)
C6: Sad, Shock (Sad Cluster)

In figure 4, it could be visible that similar emotions are adjacent. The emotions with common traits or features are classified as C1: happy cluster is related to high valence and high dominance. It aligns with a few studies, e.g., [29], where a happy group of emotions is classified in positive valence and positive dominance space. The happy cluster ranges from 0°–123°, or most of the happy group of emotions lies in the first quadrant. In the same way, the emotion wheel embodies the ranges of distinct emotions. There are debates on various emotion states (e.g., love) whether to include in the list of emotions, but we have considered whatever was provided in the DEAP dataset.

4.2. Experiments with DREAMER database

The DREAMER data set comprises EEG and ECG data of 23 participants (14 males and 9 females) through 14 electrodes. Eighteen film cuts are used to construct this dataset for eliciting nine unique emotions, i.e., calmness, amusement, anger, sadness, happiness, disgust, excitement, surprise, and fear. Each film cut goes on for a period time between 65 to 393 s, which is believed to be adequate for producing specific emotions. The information assortment starts with an unbiased film cut watching to help the participants return to the impartial feeling state in each new preliminary information assortment and serve as the baseline signals. After watching a film cut, the self-assessment manikins (SAM) were utilized to get emotional appraisals of arousal, valence, and dominance. At last, all the EEG signals are allotted with three parallel states (low/high arousal, low/high valence, and low/high dominance). The angle of each emotion's instance w.r.t origin is calculated, and some sample values are given in table 6 and the degree of every emotion for DREAMER is computed as shown in table 7. The emotion wheel based on the DREAMER dataset is shown in figure 5. This emotion wheel groups nine affective states in 6 main clusters. This dataset contains almost basic emotions which impact upon cluster formation process. These six clusters are:

C1: Happiness, Excitement, Amusement (Happiness Cluster)
C2: Surprise (Surprise cluster)
C3: Fear, Disgust (Fear cluster)
C4: Calmness (Calmness cluster)
C5: Anger (Anger cluster)
C6: Sadness (Sadness Cluster)

Table 4. Sample values (angle of each instance to the origin) of respective emotions defined in the DEAP dataset.

Emotions/Values (°)	Fun	Exciting	Happy	Joy	Cheer	Love	Lovely	Senti	Melancholy	Sad	Depress	Mellow	Terrible	Shock	Hate
V1	22.38	23.18	114.3	33.82	48.56	86.82	215.74	189.75	162.24	27.9	41.03	4.03	223.05	233.36	49.76
V2	104.46	26.1	79.28	0.97	51.94	111.79	25.16	33.82	236.16	75.66	22.52	24.08	253.81	335.78	170.29
V3	24.97	94.52	238.26	160.71	160.18	195.19	179.21	219.36	70.44	107.89	148.65	216.41	25	51.43	76.09
V4	89.49	123.73	1.26	78.44	0	39.81	136.73	89.74	125.27	177.07	62.05	90.85	137.52	332.08	213.78
V5	146.55	25.9	130.69	151.35	158.51	97.32	236.52	121.73	238.13	48.77	116.85	292.64	51.63	163.67	99.9
V6	119.77	12.7	177.62	46.68	144.04	121.96	91.75	216.57	6.44	33.49	124.42	108.66	29.15	88.73	106.44
V7	232.01	105.08	34.82	160.61	104.11	255.23	292.84	162.25	115.81	309.94	82.4	123.18	67.09	88	70.4
V8	28.66	48.44	58.87	30.68	129.64	133.82	111.56	178.75	12.81	57.48	20.38	2.18	302.33	54.25	69.53
V9	94.12	64.31	91.57	1.71	2.95	31.3	42.92	72.97	93.56	76.08	46.14	3.74	39.17	150.23	67.17
V10	49.2	110.83	169.22	56.07	59.99	115.64	112.74	200.43	77.53	184.92	127.51	177.31	82.25	76.03	31.14
V11	107.93	83.69	175.13	71.73	246.64	215.58	233.25	130.23	158.92	265.03	190.45	226.71	139.98	57.51	23.37
V12	4.43	58.04	129.35	6.3	69.62	31.06	35	218.51	120.03	116.77	142.15	35.44	193.28	268.26	291.27
V13	90.42	123.62	79.18	102.92	118.77	135.99	214.7	181.02	334.4	131.51	76.97	105.95	337.03	143.3	101.9
V14	127.96	84.89	150.86	21.81	176.83	150.53	131.13	93.48	190.14	209.37	51.68	97.91	124.45	192.55	119.53
V15	77.5	44.96	115.75	86.38	144.53	99.86	137.75	218.42	75.07	208.59	121.59	114.97	64.78	127.47	62.07
V16	167.47	55.72	70.31	27.33	91.33	182.38	253.16	37.56	67.78	221.75	79.11	206.48	73.44	111.1	217.62
V17	71.41	62.27	30.16	46.38	89.82	36.3	70.87	8.82	102.37	12.11	80.3	138.62	59.89	68.51	78.04
V18	30.22	23.19	1.06	18.95	34.22	115.27	24.3	1.45	55.47	164.38	60.13	110.63	82.16	71.12	81.88

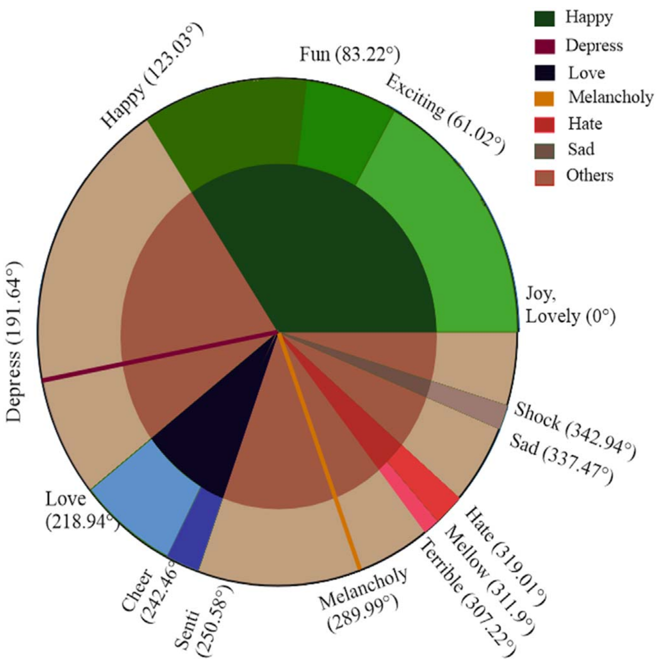

Figure 4. DEAP emotion wheel based on the degree.

5. Findings and analysis

There are two most important questions to answer for technical analysis. First, what is the prime requirement for calculating angle? The prime requirement of calculating angle is to map emotions to emotion AI devices that are able to identify an individual's emotions and recognize the emotions of the other. The unlabeled emotions or complex states of emotion can be identified through this approach. Suppose one emotion (say rage) is having an angle of 280° then according to the proposed modeling, this emotion is lying near the anger cluster of emotions. Rage emotion can have similar traits to anger emotions. In this way, emotions can be identified by calculating the emotion angle.

Second, How the emotion angle validates the emotion theory as proposed by researchers? According to a previous researcher [39], happy and sad are opposite emotions and there is a maximum angle difference between happy and sad clusters in the emotion angle wheel as shown in figure 4. As comparable to Whissell's space (figure 1), the happy cluster is lying in the first quadrant, and anger emotion is lying in the fourth quadrant. This also validates the proposed approach to analyzing emotions. For more analysis, the proposed approach is implemented on two different datasets. If we compare both emotion wheels (figures 4 and 5), then we can analyze that most positive emotions, say (happy cluster), lies in the circle's first quadrant on both wheels. We can also consider surprise in the happiness group related to high valence and high dominance (figure 5). Most negative emotions (say hate, sadness, anger) lie in the fourth quadrant. Some emotions may belong to another group, say mellow emotion may not lie in the hate cluster in the DEAP emotion wheel, which could also be variations in the labeling of emotions in diverse cultures. Nevertheless, this additionally shows the trouble of discrete linguistic labeling. The proposed approach is proved efficient as it produces almost reliable results and works on both datasets as both datasets have variations in many aspects. The VAD values in both datasets are taken in different ranges, which may impact results despite this approach performing better and analyzing various emotions. The above conclusions additionally exhibit to some degree the adequacy of the three emotion primitives, specifically Valence, Arousal, and Dominance. Even though in the DEAP database, the benefits of other aspects (Liking and Familiarity) are likewise demonstrated, however, we find that they don't give any valuable data about affective states. According to the cognitive theory, emotional states are reactions to the intellectual evaluation of a strange circumstance. Henceforth, we believe that the emotion angle wheel is adequate to represent emotions completely.

5.1. Findings

The proposed framework supplies the investigation of emotions with many notions such as evolutionary biology, functional analysis, developmental theory, the consensus of contraptions across phyla, proximate causation, and ultimate causation, and dissociative identity disorder. Cheerfully, in blend with the structural,

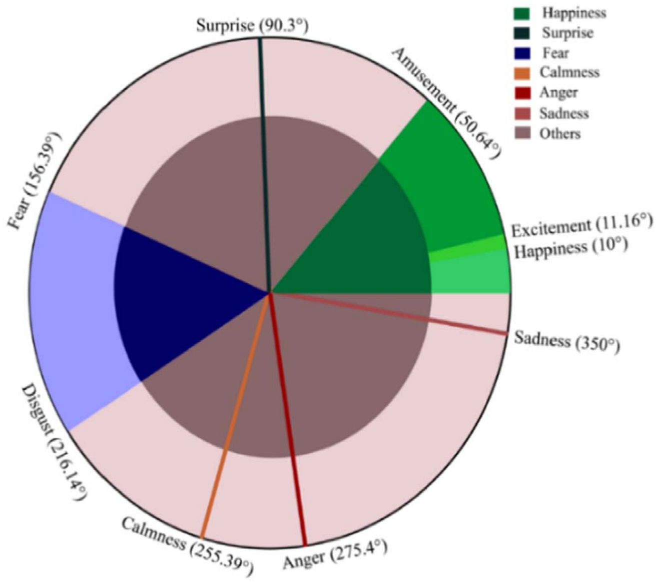

Figure 5. DREAMER emotion wheel based on the degree.

Table 5. Average Euclidian angle of each emotion to origin for DEAP

Emotions	Angle(Θ)	Group of Emotion	Angle Range
Fun	83.22°	Happy	0°–123°
Lovely	0°		
Happy	123.03°		
Joy	0°		
Exciting	61.02°		
Depress	191.64°	Depress	191.64°
Cheer	242.46°	Love	218.94°–250.58°
Love	218.94°		
Senti	250.58°		
Melancholy	289.99°	Melancholy	289.99°
Hate	319.01°	Hate	307.22°–319.01°
Mellow	311.9°		
Terrible	307.22°		
Shock	342.94°	Sad	337.47°–342.94°
Sad	337.47°		

derivative, and sequential frameworks depicted above, evolutionary biology theory can give not just an approach to getting sorted out information in the fields of emotion, character, and psychopathology yet additionally new apparatuses for clinical practice. An analyst should reveal and distinguish feelings. An evolutionary approach recommends that the subjective phenomenological states of a subject (the classes they are given) are typically more uncertain and vaguer than are the related motivations to activity. We really want not to demand, like the behaviorists, that the main apparent actions are appropriate for study; notwithstanding, instincts to activity might be tested regardless of whether the activity happens. What's more, effective transformation suggests the capacity to feel and communicate all feelings in suitable settings. Applied to feeling, the cultural directs that 'there is a period and a spot for everything' exemplifies that all feelings can be versatile inside the human culture. It involves figuring out the particular conditions in which emotions can fizzle in their versatile assignments. The psycho transformative hypothesis has directed tests for estimating moods, character attributes, inner self protections, and adapting styles. It has likewise proposed a relationship between feelings and the existential emergencies that all individuals depend on, including ordered progression, territoriality, personality, and transience.

Table 6. Sample values (angle of each instance to the origin) of respective emotions defined in the DREAMER dataset.

Emotions/Values (°)	Amusement	Anger	Calmness	Disgust	Excitement	Fear	Happiness	Sadness	Surprise
V1	57.39	260	140.75	300.56	0	140.75	57.39	205.3	203.39
V2	67.72	205.3	140.75	106.65	105.59	180	140.75	300.56	113.47
V3	53.32	173.66	105.59	92.68	0	249.76	180	92.68	140.75
V4	140.75	92.68	180	233.32	180	251.59	57.39	264.03	106.65
V5	53.32	233.32	140.75	0	74.41	180	133.31	205.3	106.65
V6	133.31	105.59	260	105.59	260	140.75	57.39	180	92.68
V7	57.39	233.32	203.39	67.72	140.75	249.76	106.65	203.39	92.68
V8	205.3	0	205.3	231.72	272.68	146	105.59	231.72	92.68
V9	57.39	233.32	180	74.41	205.3	233.32	74.41	146	140.75
V10	260	105.59	140.75	0	74.41	0	0	233.32	146
V11	0	249.76	0	251.59	67.72	180	74.41	249.76	74.41
V12	74.41	92.68	140.75	67.72	0	0	0	146	57.39
V13	74.41	249.76	92.68	251.59	74.41	146	53.32	249.76	105.59
V14	180	105.59	105.59	140.75	140.75	140.75	140.75	249.76	92.68
V15	74.41	92.68	105.59	57.39	105.59	67.72	205.3	231.72	74.41
V16	105.59	205.3	140.75	74.41	74.41	0	0	92.68	74.41
V17	53.32	0	105.59	249.76	0	146	57.39	251.59	67.72
V18	74.41	0	74.41	146	0	67.72	0	146	67.72

Table 7. Average Euclidian angle of each emotion to origin for DREAMER.

Emotions	Angle (Θ)	Group of Emotion	Angle Range
Amusement	50.64°	Happiness	0°–50.64°
Happiness	10°		
Excitement	11.16°		
Surprise	90.3°	Surprise	90.3°
Disgust	216.14°	Fear	156.39°–216.14°
Fear	156.39°		
Calmness	255.39°	Calmness	255.39°
Anger	275.4°	Anger	275.4°
Sadness	350°	Sadness	350°

6. Application of emotion in games

Research on emotions plays a significant role in non-verbal communication among humans. Emotional awareness is essential for recognizing the other's unspoken messages or sign language to make a trustful relationship. Many people suppress their emotions—powerful emotions—such as fear, anger, sad—as they do not know how to deal with these feelings. In contrast, other people repress emotions to avoid unpleasant experiences. But emotions never disappear by suppressing or repressing them, even if they influence software systems, training outcomes, and overall human experience. Therefore, the proposed approach effectively designs software models in various application areas, such as video games. Its main aim is to develop an affect-aware gaming interface to familiarize its performance according to user requirements. Our approach (shown in figure 6) will work in two stages: Firstly, gameplay will help to detect three emotional attributes- valence, arousal, and dominance, for every player. Gameplay is considered as the specific way or pattern through which players interrelate with video games. It defines different challenges to players and also tells the connection between player and game. The gameplay data can be collected either by self-reports (first-player reports) or by experts who observe players' reactions externally. This type of data collection method comes under the annotation process. Annotations are categorized as preference, class, and ratings. In preference format, players are approached to analyze an emotional involvement with at least two variations/sessions of the game) (was that level seriously captivating that this level ? Which look looks more joyful?). In rating format, annotators are approached to answer survey things given in a rating/scaling structure—which marks full of feeling states with a scalar/vector value. At last, in a class-based design subjects are approached to pick a full feeling state from a specific portrayal which could fluctuate from a straightforward Boolean inquiry (was that game level disappointing or not? is this a miserable look?) to an emotional state selection. The easiest and most direct way to

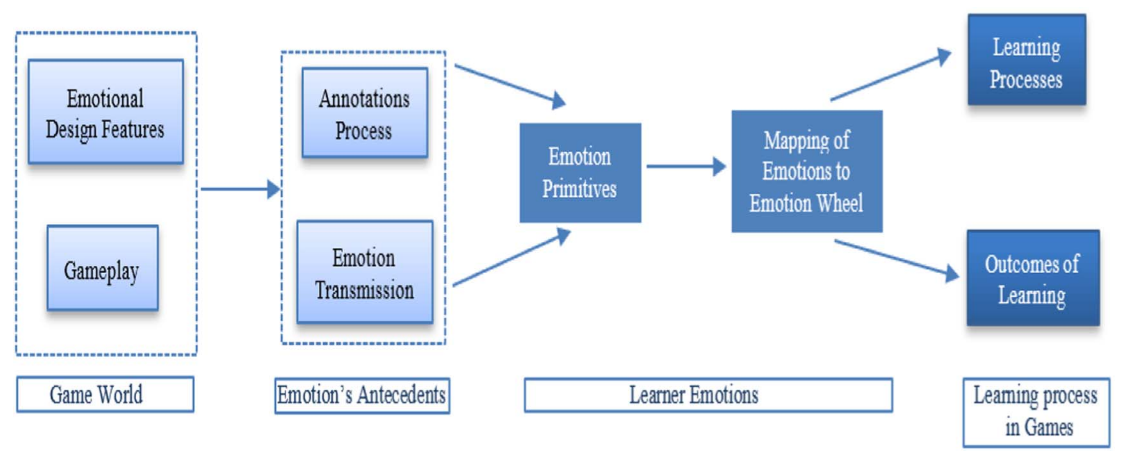

Figure 6. Model of Emotions and Learning Process in Games.

interpret players' emotions is to ask them directly about their experiences throughout playing the game. This way helps in detecting three emotion primitives VAD for each and every player. Alternatively, VAD values can be collected from game design experts in a similar fashion. Then, after getting three emotional primitives, the degree of angle will be measured with the help of the proposed approach and the emotion wheel is used to map a particular emotion cluster for the respectively measured angle. The degree of emotions will change with respect to players' emotions at each game level as the difficulty level increases progressively along with the game. In this way, a range of positive and negative emotions can be elicited by using the proposed approach—including relaxation, excitement, anger, and happiness in video games and helps game design experts to analyze various emotions of players. This can be said that feelings are major for players to profoundly draw in with games. Players' reactions in a game are impacted by their affective states. If, thus, these states could be utilized to influence the method in which the game answers, the player-game connection could be expanded and improved by extents, acknowledging full of feeling circle empowered games. Games might develop and adjust to the player in various ways and pass feelings on through an assortment of strategies and impacts.

6.1. Emotions and learning process in games

The model of Emotions and Learning Process (ELP) in Games (figure 6) aims to catch the variety of emotional states associated with learning with games and portrays common components of how feeling and learning processes collaborate to encourage explicit learning results. The model consolidates results from research on sentiments in learning with smart mentoring frameworks and also from research on sentiments in media learning. ELP shows an improvement in the adaptation of this model with the end goal of the current examinations; the complete explanation of the model is depicted by [40]. The core of the model follows the framework given by the Control Value Theory of Achievement Emotions [41], showing how the gameplay, emotional design features of games, annotation process, and emotional transmission which are predecessors of learner emotions, affect learning processes and, therefore, on results in learning with games. We will initially examine how feelings can impact learning cycles and learning results in games learning and, when relevant, advanced learning conditions, and afterward go to the emotions antecedents.

6.2. Emotions' effects on outcomes of game-based learning

The ELP model follows the Control Value Theory by depicting four motivational and mental mechanisms that are impacted by various emotions and that, thusly, affect learning results [40]. These processes incorporate attentional resource allocation, memory capacity, recovery, and critical thinking, as examined beforehand, as well as cognitive load and behavioral tendencies. Inspirational cycles are impacted contrastingly founded on valence and arousal of the accomplished feelings. Positive initiating feelings, like pride, have been found to expand inspiration to learn though pessimistic deactivating feelings, like fatigue and dissatisfaction, can sabotage inspiration [42]. Research on exploring the impact of feelings on the mental burden in game-based media learning conditions observed that positive feelings initiated by means of the visual plan of the learning materials can diminish self-detailed mental burden and support attentional focus on relevant learning material over extended periods, yet particular sorts of positive feelings, prompted through personal review, have likewise been found to have harmful effects [43] on the learning process. It is observed that emotional learning processes in games have a great impact on learners. The learners/ players who experienced delight and interest in games are occupied with more compelling critical thinking techniques than players who experienced dissatisfaction or weariness. Lastly, research on the connection of feeling and self-guideline tracked down that positive actuating emotion, as well as advancing more successful technique use as examined above, also makes players' self-guideline positive, though deactivating feelings have the contrary impact [44].

The association of the game world and the emotional learning process in ELP is upheld by meta-examinations [42], which tracked down huge good relations of learner emotions, like delight and interest, with results in a scope of computerized learning conditions, including games. On the contrary, negative emotions, like weariness, have been seen as deleterious to learning. Instances of late investigations on the connection of affection and learning remember the examination of multimedia learning conditions for which visual plan components were controlled to actuate various feelings during learning. Many researchers use virtual-reality environments (VRE) as they provide safe environments but give real-feeling scenarios to experience fears and problematic circumstances with the help of a therapist. VRE is used as painkillers by researchers as they behave like a 'new reality in which the human brain forgets the discomfort they are dealing with during surgery. The main applications of this approach are in designing games, evaluating productive work in affective computing, and creating effective affect-based software.

These discoveries showed that emotion primitives play a major role in inducing emotions through the emotional learning process in games. Many studies have since been focused on the valence primitive of emotion to determine positive emotions. Other studies focused on arousal primitive to examine whether the degree of passionate excitement in playing a game to prepare mental abilities affected results. This primitive was manipulated by utilizing various emotional design features of game characters, which initiated high enthusiastic excitement (both good and pessimistic) on one level of the game, and low excitement on another.

In outline, there has been experimental help for the impact of feeling on learning cycles and results, both in everyday learning conditions and progressively additionally in computerized games. Our approach is a model-based approach. For the model-based approach parts of the model and any boundaries that portray them are built in an ad-hoc manner and, here and there, tried for legitimacy on an experimentation premise. No artificial intelligence or complex computational instruments are expected for model-based approaches despite the fact that one could conceive the optimization of the boundary space to yield more exact models; that, nonetheless, would require observational examinations which carries the methodology more like a model-free viewpoint. The advantages of this approach:

- The emotion wheel helps analyze player emotions that comprise the notions of interest, fantasy, and challenge, leading to entertainment fused in games and also helps to analyze highly aroused emotions to help the designers make the game better for users.
- It helps people to experience all types of emotions to normalize feelings, acquire to deal with circumstances, and encounter themselves.
- It also helps users to recuperate from post-traumatic stress disorder, overcome their phobias, and get rid of drug addiction.

7. Conclusion and discussion

Emotions can be defined as mental states welcomed by neurophysiological changes, differently connected with considerations, sentiments, conduct reactions, and a level of delight or disappointment. We proposed an approach that can evaluate the correlation between different emotional states. It provides a way specialists can address the development of the entire passion experience, as reviewed through self-report. The following findings can be given from the proposed method:

- It can be inferred that affect variability can be represented in three-dimensional spaces, and emotions are related to one another as every emotion is a blend of the characteristics presented in VAD values (instead of a solitary value as defined in the categorical emotion modeling).
- It also approves the current hypothesis that the emotion wheel may be constructed based on the Euclidian angle (Θ).
- This wheel of emotion based on degree provides a means to estimate the degree of comparison between various emotion categories. It validates the existing theory that positive emotions (happy cluster) are far from negative emotions (sad cluster).

The proposed model doesn't address all inquiries regarding emotions. Yet, it starts to exhibit associations between obviously assorted areas of examination, and it recommends questions with which future exploration ought to be concerned. It gives a system to looking at or rethinking numerous issues in the field-for instance: the ontogenesis of feelings, the connection among various emotions, the idea of emotional terms in standard dialects, the impact of learning on the articulation, hindrance, and the blending of emotions and the hereditary qualities of feelings. As a future task, we will try to develop a color model of emotion as the combination of colors tell about human emotions, mood, and behavior.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/https://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html.

Conflict of interest

All authors declare that:

- This study did not receive any funding from any of the resources.
- All the authors and the submitted manuscript do not have any conflict of interest.
- This article does not contain any studies with human participants or animals performed by any of the authors.

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