# A Data-Driven Study to Highlight the Correlations Between Ambient Factors and Emotion

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**Abstract.** Emotion can be impacted by a variety of environmental or ambient factors. This means, people might show different affective reactions in response to ambient factors such as noise, temperature and humidity. Annoying ambient conditions (e.g., loud noise) may negatively influence people emotion and consequently address serious mental diseases. For this, ambient factors should be monitored and managed according to the users' preference to increase their statistician, enhance living experience quality and reduce mental-health risks. The purpose of this research is to study and predict the correlations between emotion and two ambient factors including temperature, and noise. For this, a system architecture is designed to measure user's affect in response to the indoor ambient factors. This system is tested in three experimental scenarios each of which with 15 participants. Ambient data is collected using an IoT enabled sensor network, whereas brainwaves are collected using an EEG. The brain signals are interpreted using a well-know API to recognise emotion state. Yet, two machine learning techniques KNN and DNN are used to analyse and predict emotional statues according to changing ambient temperature and noise. According to the results, DNN has a better accuracy to predict the emotional status as compared to KNN. Moreover, it shows that both noise and temperature are positively correlated to arousal and emotional status. Moreover, the results address that noise has a greater impact on emotion as compared to temperature.

**Keywords:** Emotion · Mental healthcare · Ambient factors · EEG

## 1 Introduction

Emotion is an innate and biological hardwired mechanism that promotes the survival of an organism by using adaptive responses to changing environmental circumstances [33]. This plays a crucial role in our life to respond to surrounding events. People may show different emotional statuses in various situations. For example, they feel happy when a new baby is born, excited to see a new place, or sad when they experience a break-up. However, emotion is different with


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mood. Emotion is a real-time reaction to the external events and it is usually short-term, whereas mood is the summary of the overall emotional states over a particular time period [29].

Emotional status can be recognised by behavioural, biological and/or brain signals [20]: (1) People show particular affective behaviours to respond to internal or external triggers/events [6]. For example, they might smile when they are happy or cry if they feel sad. This is difficult to recognise people affective behaviours as there is no unique behavioural emotion pattern and affective behaviours usually depend on a number of parameters such as culture, personality and/or gender [50], (2) Emotional status can be recognised using bio-signals. For example, heart-rate is increased if people are excited or surprised. However, bio-signal analysis is not able to accurately recognise emotional status as this can be influenced by a set of external factors such as illness, age and eating habits [18], (3) Brain signals (e.g., Alpha, Beta and/or Gamma signals) are measured by using Electroencephalogram (EEG) devices to recognise and study the emotional status [38]. However, this method is usually limited to experimental applications as the users have difficulty to wear EEG and feel unhappy to use it for long time.

Ambient conditions have the capacity to influence emotional statuses and address intuitive feelings, behaviours, habits or even health problems [28]. According to [54], environmental factors have the potential to address a varying degrees of behavioural problems, such as inattention, anger, and depression. This stems from the correlations of ambient factors/events and emotion and may address mental problems/issues as the results of human body's response to the surrounding environment [19]. For example, people might feel depressed or stressful if they stay in a dark room for a long time. Therefore, this is highly required to study the impact of environmental conditions on emotional statues to propose a particular correlation pattern. By this, people would be able to understand how to manage/control environmental factors such as light, noise, temperature and humidity to enhance affective experiences and mental-health conditions.

This paper aims to study the correlations between ambient factors (temperature and noise) and emotion. The key contribution of this research are outlined as below:

- Propose a data-driven experimental system architecture to collect and analyse ambient data (using an IoT enabled sensor network) and brainwaves (by using EEG).
- Test the accuracy of EEG device (EMOTIV EPOC+) and an brainwave enabled emotion recognition API by using a validated test dataset. This API is used to train and test the machine learning models which aim to predict emotional statues according to varying ambient parameters.
- Design and evaluate the performance of machine learning models in emotional status classification/prediction by using a real datasets collected from three experimental scenario each of which with 15 participants.

Under this research, three experimental scenarios including varying temperature, noise and temperature-noise are designed to study the impact of ambient factors on emotion. For this, an Internet of Things (IoT) enabled sensory system (AirRadio [1]) is deployed for ambient data collection, whereas a wearable wireless EEG equipment (named Emotiv EPOC+) is used to collect user's brain signals [45]. For each experimental scenario, brain signals are collected from 15 participants watching a (new)video while ambient conditions change. The sensory system captures and reports ambient data including temperature and noise via internet links. This research utilises a well-known emotion recognition API [42] to analyse EEG brainwaves and recognise/visualise emotional statues in real-time. The accuracy of the precensored API is tested by a validated online dataset, named SEED [61].

This paper takes the benefits of machine learning techniques -mainly K-Nearest Neighbour (KNN) [44] and Deep Neural Network (DNN) [27] to predict affective status influenced by ambient factors. The machine leaning models are trained and tested by using brainwaves collected from real participants who have been asked to wear the EEG while ambient conditions are changing. Self-descriptive questionnaires are collected to test and validate the accuracy of the proposed model.

The rest of this paper is structured as follow: Sect. 2 reviews the correlations of environmental factors and human emotion and mental-health. Section 3 introduces the research methodology and the proposed system architecture to collect and analyse recordings. Section 4 discusses the experimental results and highlights the research findings. Section 5 concludes the discussions and highlights the issues which still need to be addressed in the future.

## 2 Related Works

The relationship between emotion and (mental)health has attracted the attention of researchers during the past decades. Advances in the filed of affective computing allow us to analyse complex relationships between emotions, and external/internal factors such as environment and health [37]. Many studies have shown that physical symptoms often accompany emotional experiences [10]. This suggests that there might be a correlation between negative emotional statues and mental/physical health risks and diseases [31]. For example, negative emotions such as anger, anxiety and depression, may address serious cardiovascular diseases [51].

This is important to study the correlations of emotions and ambient factors to reduce/manage health risks. Positive emotions can significantly reduce the probability of stress and mental diseases such as depression [4], and thus improves mental health which has a great impact on family and society health and safety. In addition, many studies have shown that positive emotions address beneficial effects on general and physical health [46]. For example, this research [8] with an experimental sample size of 2000 participants over a period of 10 years reports a reduced 22% heart attacks ratio in positive emotion people. This supports that emotions have a high impact on people's mental and physical health.

### 2.1 EEG for Emotion Recognition

EEG is commonly used to collect brainwaves and recognise emotion. This captures and reports the brain neurons' voltage by using electrodes which measure the activities of multiple neurons in the brain cortex [45]. It usually measures frequencies ranging from 1 to 80 Hz with amplitudes ranging from 10 to 100 μV [22]. These signal frequencies are divided into different frequency bands, and certain frequency waves are more prominent in certain emotional states. The most important frequency waves are alpha (8–12 Hz), which is associated with brain inactivity, and beta (12–30 Hz), which is associated with active mental states [25].

The EEG signals are processed to extract emotional-related features, namely high/low arousal. For example, happiness is a state with high arousal, and the sadness is a state with low arousal [45]. However, the signals may still need to be filtered in advance to remove noise an enhance the signal quality.

Emotiv EPOC+ is one of the widely used EEG devices designed and released by Emotiv [16]. This head-mounted EEG device has 14 data collection electrodes that are positioned and tagged according to the standard of international 10–20 system [48]. As mentioned above, alpha and beta waves play a vital role in arousal measurement in emotion monitoring experiments and have the capacity to determine the level of brain activities. As [2] shows, AF3, AF4, F3 and F4 are the most commonly used locations for recording alpha and beta EEG signals in actual measurements. They are placed in the prefrontal cortex which plays a crucial role in emotion regulation. The electrodes monitor and measure the electrical signals and machine learning techniques are used to identify and predict emotional statues.

### 2.2 Machine Learning and Emotion Recognition

Machine learning (ML) techniques are increasingly being used to analyse, recognise and predict emotions. ML is used to analyse text and recognise the writer's emotional status. [49] takes the benefits of ML to categorize affective texts in children's books to achieve a better text-to-speech synthesis. This technology is used in teaching and learning applications to enhance the learning and students achievements as it has the capacity to emotionally engage students and teacher in learning [3]. Yet, ML can be used to recognise emotional statuses through behavioural cues such as facial expression [24]. Indeed, ML analyses and classifies the facial expressions/affective features which are captured/extracted using cameras.

ML techniques can be used to analyse brainwaves and recognise emotional cues. Brain signals are a key source to convey accurate cognitive and affective information [41]. They are divided into four waves according to their frequency: Delta, Theta, Alpha and Beta [57]. Brainwaves can form different emotional cues [55]. This addresses emotion recognition problem as a multi-category classification that should be resolved by using machine learning techniques. [14] analyses and compares a variety of machine learning techniques including Support Vector Machine (SVM) [17], K-nearest neighbour [44], Linear Discriminant Analysis [52], Logistic Regression [13] and Decision Trees [36].

[53] proposes two neural network models, namely simple deep and convolutional neural network, by using an EEG enabled dataset, called DEAP [53]. The results show that neural network can be an effective classifier for EEG signals, even more than the conventional machine learning techniques such as SVM.

[35] proposes an emotion prediction method combined with reinforcement learning. This is used to predict real-time emotional status during an online training to enhance the results of an online learning. It results in significant time reduction and achieves outstanding learning result and performance.

### 2.3 Environment and Emotion

Ambient factors include temperature, humidity, noise, light, and smell have the potential to influence people emotional statues. [11] studies the correlations of ambient noise on emotional statues. This aims to utilise a probability-based approaches to study the relationship between ambient factors and emotions. [23] reports that there is a close relationship between thermoregulation and emotion. According to this, environment temperature has an impact on the body regulation with a further impact on people's emotions [43] reports that higher temperatures significantly reduced happiness. Noise has the capacity to impact on emotion [7]. To support this, [40] addresses that loud noise negatively influence people emotion. Continuous high-volume sound treats mental health and may subject to harmful risks such as suicide. In addition, emotion can be influenced by ambient humidity [56]. This shows how humidity significantly impacts on students' happiness. Yet, ambient smell is taken into the account as an influential parameters on emotion. [9] shows environmental smells in public areas such as airport has the potential to affectively influence passengers.

The literatures address that a variety of ambient factors have the capacity to impact on mental health. Ambient conditions influence emotional statuses and consequently address mental health issues. There are a number of new and modern technologies to collect human brain wave data, and study how they are influenced by ambient factors such as noise, humidity and temperature. However, there is still a lack of applied research to analyse the correlations between ambient factors and emotions. This research utilises wearable EEG collection devices to collect emotional state changes of multiple participants in different environments, and use a variety of machine learning methods to highlight the specific correlations between ambient factors and emotions.

**Fig. 1.** EMOTIV EPOC+ device

# 3 Methodology

## 3.1 Experimental System Setup

This research proposes and deploys an experimental system architecture consisting of four key components including: ambient data collection, EEG data processing and analysis, self-feedback and machine leaning analysis.

An IoT enabled sensory network of AirRadio [1] devices is deployed to collect ambient data including temperature and noise. To manage the ambient conditions, small indoor cabins are equipped with air conditioner and Dolby speakers to change two ambient factors including ambient temperature and noise.

To analyse emotion, a wearable EEG equipment is used to collect and interpret user's brainwave. EMOTIV EPOC+ (Fig. 1 [16]) is one of the most widely-used low-cost wireless electroencephalography (EEG) [5]. It consists of 14 data-collection and 2 reference electrodes (AF3, F7, F3, FC5, T7, P7, 01, 02, P8, T8, FC6, F4, F8, AF4) that are labelled according to international 10–20 system of electrode placement [26]. Using EMOTIV EPOC+, five basic emotional states including happy, sad, fear, anger, surprise, and disgust are recognised.

Under this research, EMOTIV EPOC+ is used to collect brain signal for 15 participants who watch a video while changing ambient factors(temperature and noise). In turn, an open source and real-time emotion recognition API [42] is used to process and analyse the collected EEG data. This classifies input EEG dataset into five primary emotions including fear, happy, neutral, sad, relax according to the Russel's circumplex model of affect [47] and [62] (see Fig. 2).

To test the functionality, correctness and reliability of the emotion classification API, a validated online dataset, named SEED [61], is used. SEED dataset is an EEG dataset collected by Shanghai Jiao Tong University. This dataset contains EEG data from 15 groups of subjects, while watching affective videos labelled (based on arousal level) as negative, neutral and positive [32]. SEED is used to test the performance and accuracy of emotion recognition API. According to the results, this API is able to address an accuracy of 69.1% in emotion recognition. Yet, SEED is used to test the accuracy of EMOTIV EPOC+ EEG. For this, SEED data features are labelled according to EMOTIV EPOC+ channels and then the accuracy of emotion recognition is measured. According to our

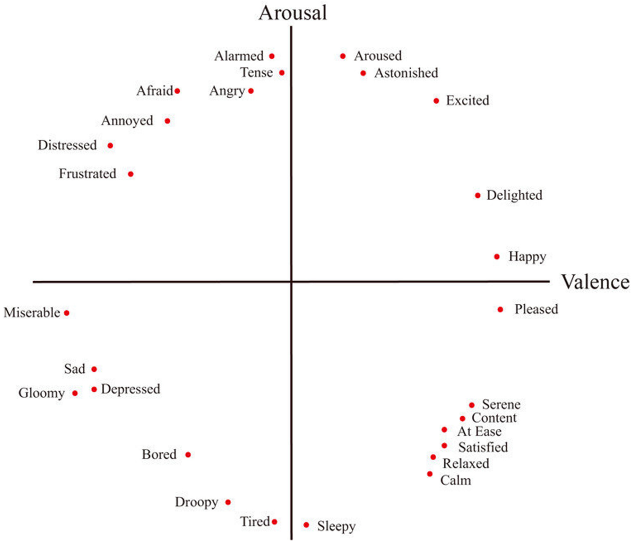


**Fig. 2.** Russell's circumplex emotion model

results, our EMOTIV EPOC+ is able to recognise correct emotional status with 72% accuracy.

A questionnaire is designed to collect user's self-describing experience and/or feedback at the end of each experiment. This allows to collect and analyse user feeling and recognise external factors -mainly background information which may influence the user's emotion and the experiment quality.

### 3.2 Experiment Design

This research aims to study the correlations between ambient factors-mainly temperature and noise and user emotion. Ambient factors are the research independent variables which change during each experiment, whereas emotion status is an dependent variable that is measured accordingly.

As Fig. 3 depicts, user data is collected in two forms: an online questionnaire and EEG. The former is a self-describing form to provide user's information and feeling during the experiments, whereas the latter collect user's brain signals to recognise the emotional status. User data is collected from 15 participants for each experiment. AirRadio sensor captures ambient data samples and forward the results to the system for aggregation and further analysis in real-time. The collected datasets are analysed and visualised to explore the correlations between ambient and affect data features. Yet, machine learning techniques including KNN and DNN are used to classify the predict the affect states according to ambient data change.

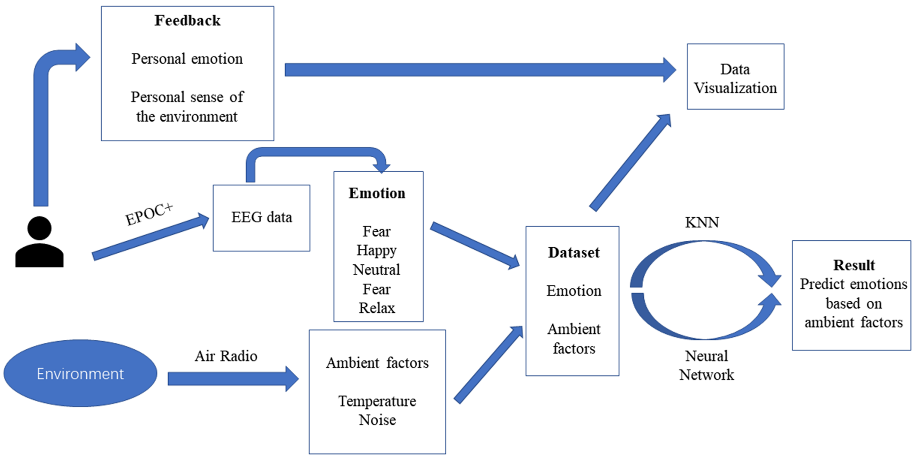


**Fig. 3.** The proposed experimental system architecture

To study the correlations between ambient factors and emotional status, three scenarios are designed. As Fig. 4 shows, the experimental scenarios (groups) are formed according to changing variables including (1) active temperature, as this changes while noise is fixed (no noise), (2) active noise, as it changes while temperature is fixed (standard indoor temperature), (3) active temperature and noise, both noise and temperature change. Each experiment includes 15 participants who participate in EEG data collection. They are asked to watch a documentary movie while ambient factors change. Each movie introduces a new and non-visited Chinese city in 10 min for each participant. This means, each participant watches a new city documentary that never visited or seen. Indeed, the participants are selected from a same age range 20–21 years old (male) and with no prior knowledge of the video content to minimise the impact of external parameters (e.g., gender, age and background knowledge) on the experimental results. As Fig. 7 and 9 show, ambient data including temperature and noise linearly change during each experiment and according to a particular range. This allows to study how people emotion changes if ambient noise and temperature change behind the comfort level (e.g., 20–22 centigrade degree for indoor temperature and 45–55 dB for indoor comfort acoustic level [30] and [12]). AirRadio sensor network reports ambient data samples each 10 s for aggregation and further analysis. At the same time, EEG data is collected from the participant with a 10-s time window for classification and analysis. KNN and DNN techniques are used to recognise the correlations between the ambient factors and emotional status. They are utilised to classify/predict the future emotional status according to ambient data changes.

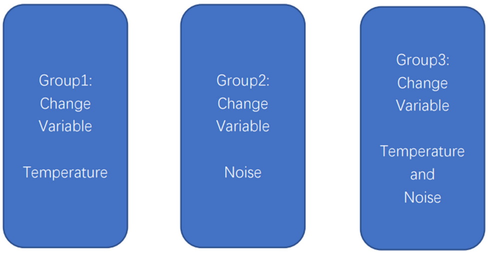


**Fig. 4.** Experimental scenarios

**Machine Learning.** This research utilises two machine learning technologies including k-nearest neighbours (KNNs) [44] and Deep neural network (DNN) [27] to analyse the collected EEG data, and predict the emotional statues corresponding to environmental conditions. For this, the experimental dataset is randomly partitioned into training (70%) and test (30%) datasets. Two machine learning models including to KNN and DNN are trained using the training dataset and used to label (predict the emotion value) test dataset. According to our results, the accuracy of KNN and DNN for emotion classification/prediction respectively are 71.19% and 74.57%. Hence, this is achieved that DNN has better precision performance to predict emotional status influenced by ambient factors as compared with KNN. Accuracy is calculated as the number of correct predictions over the total number of predictions.

**KNN Machine Learning.** Supervised learning is technique to extract the features of observed datasets to form an prediction model according to the application's objectives [34]. Indeed, supervisor learning utilises labelled data samples as a training datasets, and iteratively make predictions until the objectives are achieved [59]. There are two well-known supervised learning algorithms, linear support vector machines (SVM) [39] and k-nearest neighbours (KNN) [44], which are used in the literatures to study the correlations between datasets [21] and [2].

This research utilises k-nearest neighbours (KNN) [44] to classify emotional statuses and predict ambient-affect correlations. As Algorithm 1 shows, KNN recognises K nearest values (neighbours) in the dataset, and determines the most fitted emotion classes according to the value popularities [60]. For this, KNN machine learning model is proposed and trained to predict the affective status according to changing environmental factors. This addresses two phases: model training and test. For model training, the collected data from the users form a training dataset which is used to train KNN model. For the test phase, environmental factors are formed as the model's input, whereas five emotional states (fear, happy, sad, neutral and relax) are the machine learning model's output (classification labels).

```
Require:
  /*the coordinates of n training samples*/
  A[n];
  /*the nearest neighbour number*/
  k;
  /*new sample*/
  x;
Ensure:
  /*the class/label of x*/
  k_labels;
  /*initial k nearest neighbours of x*/
  A[1]~ A[k];
  /*Calculate the Euclidean distance between the test sample and x*/
  d(x, A[i]): i = 1, 2..., k;
  /*Sort d(x,A[i]) in ascending order*/
  Sort (d (x, A[i]));
  /*Calculate the distance D between the furthest sample and x*/
  D = Max (d (x, A[i]));

  /*Calculate the Euclidean distance between A[i] and x*/
  for i = k + 1; i <= n; i + + do
    d (x, A[i]);
    if d(x, A[i]) < D then
      Replace the farthest sample with A[i];
      /*Sort d(x,A[i]) in ascending order*/
      sort (d (x, A[i]));
      /*Calculate the distance D between the furthest sample and x*/
      D = Max (d (x, A[i]));
    end if
  end for

  /*Calculate the probability of first k samples belong to category*/
  k_labels = label (A[Top_k_index]);
  /*The class with greatest probability is the class of sample x*/
  Result = Max_prob(k_labels);
```

**Algorithm 1:** KNN Algorithm

**Deep Neural Network.** Deep neural network (DNN) [27] has the capacity to discover the coherence of input data features by adding an appropriate number of hidden layers to Feedforward Neural Networks. This uses a certain threshold value in output layer to address the label classifications. Neural network is an extension based on perceptron, while DNN is formed as a neural network with many hidden layers. Hence, DNN can be considered as a multilayer perceptron (neural network).

Multi-layer perceptron (MLP) [58] is a Feedforward artificial neural network model, which maps multiple input data sets to a single output data set. Hence, MLP consists of nodes as multiple layers (input layer, hidden layer, and output layer) which are fully inter-connected. By this, MLP's forward propagation algorithm utilises the output of the previous layer to calculate the output of next layer. This uses several weight coefficient matrices (W) and bias (b) to carry out a series of linear and activation operations according to an input value vector (X). The calculation starts from the input layer, and sweeps the layers one-by-one until the output layer is reached and the result is calculated. The weight W and bias b are learned through back propagation. The objective is to minimize the difference between the predicted output and the expected output. For this, unknown input-output relationships are approximated by back propagating output layer errors into hidden layer [15].

This research proposes a network structure consisting of three layers: input layer, hidden layer and output layer. According to our results, three levels for hidden layers with 20 nodes work the best for this experimental plan. The input is the temperature and humidity of the 2 characteristic data environments, and the output is the 5 emotional categories (fear, happy, neutral, sad and relax). Figure 5 shows, the proposed DNN with three levels of hidden layers designed for the experiments.

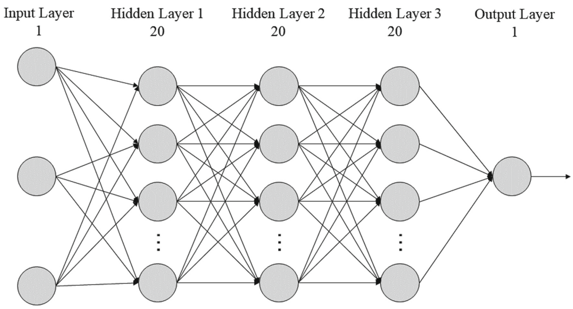


**Fig. 5.** Structure of DNN

## 4 Results and Discussion

This section discusses the experimental results to highlight the impact of ambient factors on emotional statues. According to experimental design, there are there categories for changing variables including noise, temperature, and temperature-noise. Each category aims to study the impact of the changing variable(s) on the emotional state. By this, the result of each category is presented to highlight the correlations of changing variables and emotional states. Figure 7 depicts temperature value is linearly reduced from 30.5 °C to 22 °C, whereas Fig. 9 shows how the noise level linearly changes during the experiment from 35 dB to 70 dB.

This research utilises data aggregation for data pre-processing and study the impact of ambient factors on emotional status. For this, a time-based Average aggregation function is used for environmental data to calculate the average of each ambient value from each experiment cabin (user indoor area) according to a particular timing plan (10 min experiment). Emotional statues are aggregated according to a Mode function. For this, emotional statues of each user are collected and listed as a vector. In turn, a mode value is calculated to update the dataset and machine leaning model training [62].

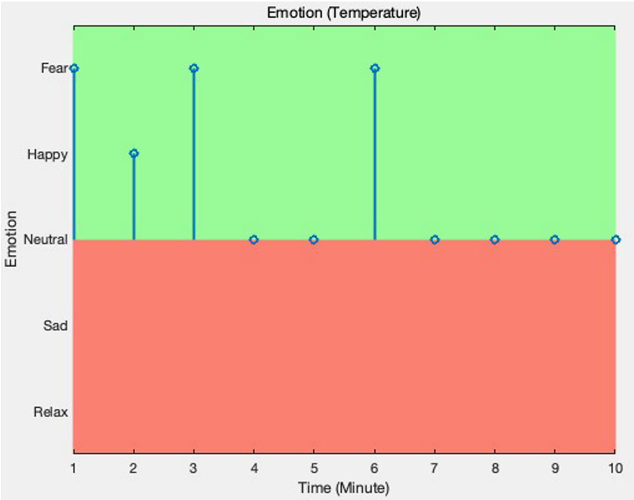


**Fig. 6.** Mode of participants' emotional statues (varying temperature)

### 4.1 Varying Temperature

As Fig. 6 shows, user emotional status can be influenced by indoor temperature. In other words, the users are emotionally behave to do a particular task if indoor temperature changes during the experiments. The participants start the experiment with a particular psychological state (e.g., fear as (mode)emotional state for the majority of participants). This stems from the fact that they feel strange to join a new experiment in which they should watch an unseen video of an unknown city. Yet, they may feel uncomfortable due to the high indoor temperature as Fig. 7 shows. However, the participants' emotional states change (fear to happy) and they gradually become neutral for a while (until 6) as they fully engaged with the movie, adapted to the experiment and environment and the temperature meets the indoor comfort level. This supports that the participants feel happy when they feel safe and convenience after several minutes watching a video where indoor temperature is not high.

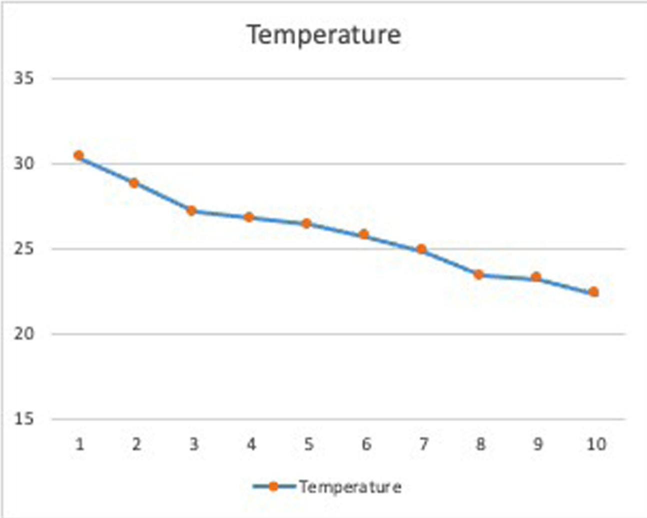


**Fig. 7.** Temperature chart

According to the results, this is found that emotional statues become happy (low-aroused) and/or neutral (no-aroused) when the ambient temperature drops from high to more comfortable values. This means, people feel uncomfortable and experience high-aroused emotional status such as fear when the temperature is high such as 30 °C. However, their affective status will become happy and then neutral if the temperature gradually decreases and meets the indoor comfort level. According to Fig. 6, indoor thermal comfort level rage [30] is supported and the participants experience happy and neutral emotional state when indoor temperature meets the comfort level 22 to 24 °C.

### 4.2 Varying Noise

According to Fig. 8, there is a certain relationship between the environmental noise and the participants' emotional state and the participants are emotionally influenced by varying noise. As the result show, participants mostly experience happy emotional status during the first minutes of the experiment when there is no or low level of noise. However, they feel affectively aroused-mainly fear if ambient noise is increased. They feel neutral and there is no significant affective change for a while when the noise level meets the acoustic comfort level (45–55 dB) and the participants are adapted to the ambient nose level. However, they feel aroused and feared again when the ambient noise level is significantly increased and reached around 70 dB.

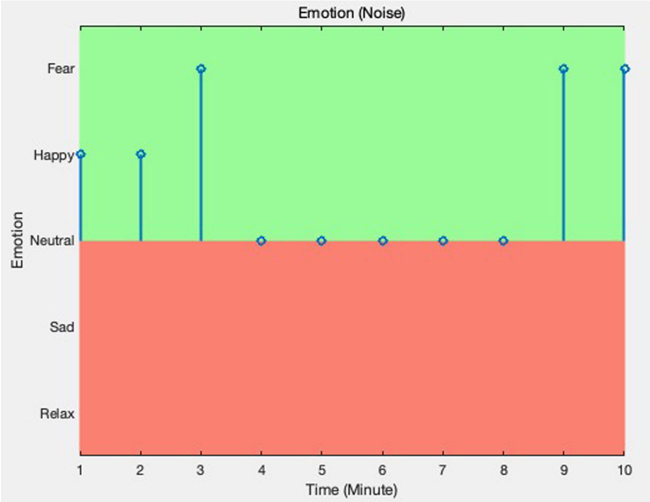


**Fig. 8.** Mode of participants' emotional statues (varying noise)

As results show, the participants experience aroused-emotion such as fear when the noise is suddenly increased. The emotional states are gradually changed to neutral if they are adapted to the ambient noise which is slowly increased. However, they feel fear and/or highly aroused when the noise level is highly increased and reaches around 70 dB. This supports that high-level noise (e.g., 70 dB) is annoying, addresses high-aroused emotion such as fear [28].

### 4.3 Varying Temperature and Noise

Simultaneous changing ambient factors has the capacity to influence users' emotions. As Fig. 10 shows, the participants' emotional statues are influenced if both temperature and noise change at the same time. During the experiment, both the ambient parameters gradually change while the participants run experiment and watch the video. Temperature is reduced from 30 °C to 22 °C, whereas ambient noise is increased from 35 dB to 70 dB. According to the results, the mode of participants emotional statues remains neutral and/or sad (low arousal) during the first two minutes of the experiments. In other words, the majority of the participants experience sad emotion when the temperature is decreased into indoor comfort level and noise is increased. The results show a similar emotional behaviour and the participants feel neutral (or sad) if the temperature is decreased to meet indoor comfort level, but the increasing noise is still in a standard level. However, they feel aroused (e.g., fear) when the noise level is highly increased (70 dB) and annoys them during the experiments. They feel fear even indoor temperature meets comfort level. This means, noise has a greater impact on emotion as compared to temperature.

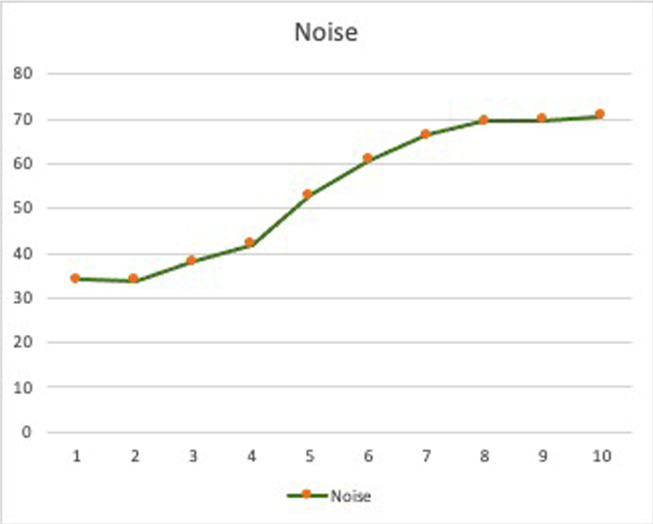


**Fig. 9.** Noise chart

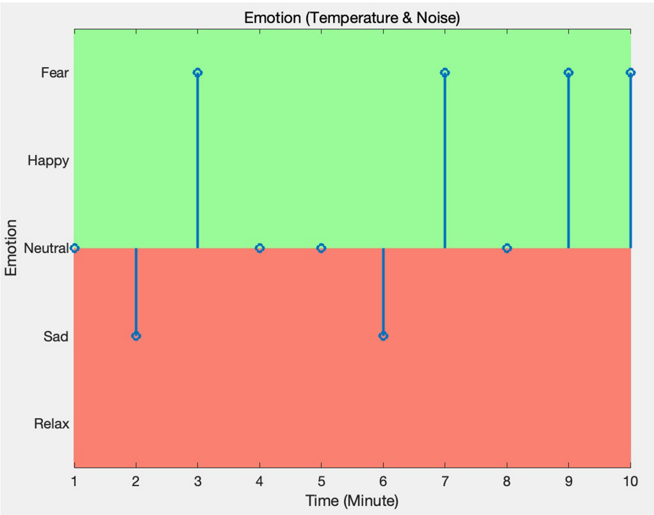


**Fig. 10.** Mode of participants' emotional statues (varying temperature and noise)

## 5 Conclusion and Further Work

This research focuses on a data-driven study to highlight the impact of ambient factors on emotional status. This has the capacity to offer mental healthcare teams a number of benefits to understand how emotion is influenced by varying ambient factors. Indeed, this research highlights the impact of ambient conditions on people affective behaviour when they respond to changing environment while doing a particular task such as watching a video. Under this research, EMOTIV EPOC+ EEG is used to collect brain signals from three experimental scenarios including varying temperature, noise and temperature-noise. 15 participants join each experimental scenario to wear the EEG and watch a never-seen documentary movie for 10 min. The EEG collects brainwaves are measured using (labelled) electrodes to recognise five basic emotional statuses (Neutral, Happy, Sad, Fear and Relax). At the same time, a sensory system (AirRadio) collects and reports real-time ambient data including temperature and noise. The collected ambient data is used to study how they influence emotional statuses. This research utilises KNN and DNN to analyse and predict emotional status according to the ambient variables. DNN works better when the hidden layer is set as 3 layer, and the nodes are 20. According to the results, 71.19% and 74.57% of accuracy are respectively achieved for KNN and DNN learning predictions.

The experimental results support and highlight the correlation of environmental data and emotion. None or limited increased arousal (neutral or happy) is observed if the ambient temperature is decreased form high to meet indoor comfort level, whereas people experience high aroused emotional statues when environment becomes hot. Yet, the participants feel feared and high aroused when the ambient noise become annoying (over 70 dB). According to the results, temperature has a greater impact on emotion than noise in varying temperature-noise scenario if the noise (30–65 dB) is not too high. For this, emotion changes according to the varying temperature and with no influence of noise. However, noise becomes the key reason to change the emotional statues and makes the people aroused if it reaches 70 dB. For this, the user emotionally experiences a minimum impact of temperature.

In future, a new experimental plan should be designed with an increased number of tasks during a longer experiment time. By this, the experimental dataset includes a greater number of data features to highlight the impact of ambient factors on emotion. Indeed, this allows machine learning techniques to form a more accurate prediction model which supports a greater number of states per each action.

Wearable sensory devices such as Galvanic Skin Response (GSR) can be used in the future to enhance the accuracy of emotional recognition. This helps to measure the human bio-feedback in affective cases influenced by external factors such as ambient conditions. This may returns better results as compared to EEG because bio-feedback sensors usually are easier to wear and carry.

The impact of ambient factors such as occupancy and pollution on emotional status also can be addressed as future work. The ambient factors should be collected using a sensor network to report the air pollution and real-time occupancy. At the same time, brain signals should be recorded to observe how they change according to the variety of the ambient factors.

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