Education and Information Technologies (2023) 28:11193–11219
https://doi.org/10.1007/s10639-023-11619-6

Examining the relationship of personality traits with online teaching using emotive responses and physiological signals

Jaiteg Singh[1] · **Resham Arya**[1]

Received: 7 October 2022 / Accepted: 23 January 2023 / Published online: 14 February 2023

Abstract
In the education sector, there is a rapid increase in using online teaching and learning scenarios. Making these scenarios more effective is the main purpose of this study. Though there are a lot of factors that affect it, however, the primary focus is to find out the relationship between a teacher's personality and their liking for online teaching. To conduct the study, a framework has been proposed which is a mixed design of self-reported (emotions and personality) data and physiological responses of a teacher. In self-reported data, along with teachers, learners' perception of a teacher's personality is also considered which explores their relationship with online teaching. The final results reveal that teachers with a high level of agreeableness, conscientiousness, and openness personality traits are more comfortable with online teaching as compared to extraversion and neuroticism traits. To validate the self-reported data analysis, the physiological responses of teachers were recorded that ensure the authenticity of the collected data. It also ensures that the physiological responses along with emotions are also good indicators of personality recognition.

Keywords Education · Online teaching · Personality · ECG · GSR · fEMG

1 Introduction

Online Teaching (OT) has become an essential part of the education sector. It is another way of providing education to learners through virtual platforms (Yu, 2021). In comparison to offline, online provides many benefits such as flexibility of time and place, cost-efficiency, ubiquity, and ease of accessibility (Evans, 2014). For OT, there is no need to be physically present anywhere. It saves the cost and time of

✉ Jaiteg Singh
jaitegkhaira@gmail.com

1 Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India

commuting, building resources, and maintaining infrastructure. In addition to this, it also gives learners the facility to access the course at any time from any place (Starr-Glass, 2013).

However, with these advantages, the sudden transition from Offline to Online has brought several challenges for teachers and learners also. On the learner's side, their less engagement in the course, lack of attentiveness, unaffordable technology and internet unavailability in rural areas, plagiarism in assessment tasks, etc. are the multiple issues that have been reported by many researchers (e.g. Borg et al., 2021; Maican et al., 2019; Scherer et al., 2021). It may somewhere lead to a low retention rate of learners in OT as compared to offline.

Another side, at teacher part, it has been found that some of them believe that with OT, there is an increase in a communication gap between them and learners as no face-to-face interaction exists which limits the supervision of students in the classroom (Martin et al., 2019). Some of the teachers also did not have the proper resources and were not familiar with tools and technologies. Due to this, the effectiveness of teaching and learning suffered a lot when OT took place (Maican et al., 2019). But, on the opposite side, some teachers adapted the OT scenarios more comfortably as they give them the flexibility to work, more confidence, and courage to teach as no face-to-face interaction takes place (Svendsen et al., 2011).

Therefore, it could be assumed that the adaption of the OT scenario is subjective to the personal factors of a teacher. These factors include personality, perception, liking, emotions, or sentiments. In other words, to make an OT scenario a big success, the relation between the teacher's personality and their liking of the Online method of teaching needs to be examined critically.

1.1 Need of physiological responses

A few researchers have already analyzed these factors like personality, age, and gender, but based on questionnaires only (Yu, 2021; Grieve et al., 2019). At some point, their results are also contradictory because self-assessment-based data always give biased results (Miranda-Correa et al., 2021). For instance, in one research it has been found that learners with extrovert personality traits are more comfortable with OT and another research reports the opposite truth i.e. learners with introverted personalities are much more suitable for OT. Therefore, in this paper, the teachers' personalities, perceptions, and emotions are analyzed and validated to address this gap.

1.2 Aim of the study

The present work aims to analyze the teacher's personalities from their self-reported values as well as from the learner's perspective also. Further, they are validated on the base of the teacher's physiological signals as they are uncontrollable factors and give genuine results. For self-reported values of personality and emotions, a big five-factor questionnaire (Donnellan et al., 2006) and Self-Assessment Manikins (SAM) form is used (Bradley & Lang, 1994). To capture the physiological parameters, Electrocardiography (ECG), FEMG (Facial Electromyogram), and GSR (Galvanic Skin Response) sensors are used.

To achieve this aim, a framework is designed that analyzes the emotions, personality, and suitability of a teacher for an OT. Its working is divided into sub-parts.

1. Investigating a teacher's personality from a learner's perspective.
2. Investigating a teacher's personality from their perspective in combination with their emotions for OT.
3. A framework for validating teachers' personalities using physiological signals through case analysis.

To achieve the complete goal of this work, the paper is divided into multiple sections. Section 2 describes the models related to personality along with a brief description of physiological signals. It also shows the background work done related to OT and personality prediction using physiological signals. Section 3 explains the methodology adopted for the investigation of personality using two different ways. It also presents the framework that has been designed for Further, Section 4 shows the results obtained following the Conclusion and Future work in Section 5.

2 Background

In this section, firstly information about personality traits, physiological signals, and their models or measures is given. After that, background work related to making OT scenarios more effective is discussed. With this, the research linked to physiological responses that ensure them as good indicators for personality prediction is also presented. In the last of this section, the hypothesis that is going to be proposed for the current work is briefly mentioned.

2.1 Personality and its measures

Personality is a human characteristic that can be described by various parameters and makes every individual unique or different from others (Butt et al., 2020). For assessing personality, various theories and models have already been designed such as PEN (Psychoticism, Extraversion, and Neuroticism) model (Basu et al., 2018), Big five-factor model (Arispe & Blake, 2012), NEO-FFI (NEO- five-factor inventory) (McCrae & Costa, 2004), and MBTI (Myer Briggs Type Indicator) (Ismail et al., 2017). Among these models, for the current work, a very famous Big five-factor model is used. It measures personality into five dimensions—Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. It is also known as the OCEAN model. For more understanding, these personality dimensions are mentioned with some of the characteristics with low and high values as shown in Table 1. For instance, if the person is low extraversion, he must be having quiet and reserved traits of personality. Similarly, if the person is highly extraversion, he must

Table 1 Personality traits and their features

Low score	Personality trait	High score
Silent, Reserved	Extraversion	Loquacious, Sociable
Doubtful, Uncooperative	Agreeableness	Supportive, Approachable
Careless, Inattentive	Conscientiousness	Organized, Reliable
Peaceful, Secure	Neuroticism	Anxious, Sensitive
Cautious, Negligent	Openness	Imaginative, Original

be talkative and sociable. This way all other dimensions are mentioned. To measure these traits, a 7-point Likert scale is used in the current work.

Along with personality, in the second approach, the teacher's perception of OT is also collected. It includes liking as well as emotions reported by a teacher for OT. For this, the most common and easiest approach i.e., Self-Assessment Manikins (SAM) is used (Bradley & Lang, 1994). In SAM, emotions are conveyed in two categories of Valence and Arousal.

2.2 Physiological modalities

Physiological signals are used to measure the various activities occurring in the human body related to the heart, brain, sweat gland, facial muscles, blood pressure, etc. However, the current work analyzed the heart, sweat glands, and facial muscles only which are explained below.

1. Electrocardiogram (ECG): ECG is the process of recording the electrical activity of the heart and is measured by placing electrodes over the skin. It records the signal from the heart that flows from the upper right of the body toward the lower left of the body (Hasnul et al., 2021).
2. Galvanic Skin Response (GSR): It indicates the variations in sweat gland activity that reflects the intensity of our emotional state known as emotional arousal (Yu & Shouqian, 2020).
3. Facial Electromyogram (fEMG): It indicates the degree of muscle contraction or measures electrical activity that reflects due to the nerve's stimulation of the muscle on the face. It is also used to find the correlation between physiological responses and cognitive emotion (Pushpa Latha et al., 2013).

2.3 The reason behind considering these signals for the study

For the current work, only three physiological responses that are ECG, GSR, and fEMG are considered by keeping in mind a teacher's comfort. As teachers have to apply these sensors while taking online classes, therefore as compared to blood pressure, and electroencephalography, the three sensors GSR, fEMG, and ECG were more convenient. In addition to this, cost constraints were also taken into account due to which these three physiological parameters have been chosen.

2.4 Related work

This section summarizes the work done by various researchers to make scenarios of OT a success for teachers as well as learners. Following that, it also shows the work done for personality identification using physiological signals. From this survey, it is also ensured that the physiological parameters play a major role in investigating the role of personality.

2.4.1 Previous work done in OT

Over the last 3 years, many educational institutions have adopted online platforms for teaching students. Due to some unavoidable circumstances like COVID-19 where a complete lockdown happened and no one was allowed to go outside. Then it became mandatory in the education sector to adopt online teaching. Parallel to adaption, research on making this OT more effective was also taking place. Here are some of the studies that stated a lot of factors for an effective OT and are further explained.

It has been found that instructor quality plays an important role in OT scenarios, as it is directly related to the student's satisfaction. If students are enjoying the learning, then the OT is a big success (Martin et al., 2018). Other than this, curriculum design also hampers the effectiveness of Online learning. If the course content, course structure, educational goals, etc. are not properly designed the students will not get any benefits from the OT (Almaiah & Alyoussef, 2019). One study suggested that the content which is to be delivered during OT to students should be creative. Video-based content and recordings help students a lot in learning and they can have access to all the lectures anytime which is an effective way of learning (Mishra et al., 2020). In (Setiana et al., 2021), various factors have been explored that reduce the interest of students in online learning so that necessary action could be taken place.

However, on the other part, for some students, an OT is the best way of providing education with all the comforts of time and space. They consider it an easy and cost-effective way of learning. They give facilities to students to learn the course from any place at any time. (Muthuprasad et al., 2021; Kaup et al., 2020). With all the comforts for students, teachers found difficulty in supervising students also. How much control they have in the class matters a lot (Mukhtar et al., 2020). Therefore, on the teachers' part other than their teaching methodologies, research on their factors like personality and emotions is also required. In (Yu, 2021), work on the effect of education level, gender, and personality on OT outcomes has also been observed that reveal the impact of multiple traits of learners on their learning outcomes but much more analysis is required on the teacher's part. This paper (Noreen et al., 2019) also discusses the impact of a teacher's personality on students' achievement, but a deep analysis is again required for the same.

Thus, in the current work, teachers' personality has been investigated from their own as well as students' perspective to find a relationship with their liking for OT. Also another factor i.e. physiological signals have been taken into consideration that ensures they are the best predictors of personality. They have been analyzed in combination with emotions also which gives good results for personality prediction. In the next section, a review of personality prediction using physiological signals is presented.

2.4.2 Personality recognition using physiological signals

This section presents information regarding the previous work done on personality prediction using physiological signals in Table 2. This information comprises various data like used physiological measures, applied filters, relevant extracted features, machine learning models, and final results. These columns are equivalent to the flow of the personality prediction system which is further explained in the methodology section.

From this table, it can be concluded that physiological signals are good indicators of the personality of a human being. These signals are uncontrollable and could be a reliable measure for knowing more about human behavior. Therefore, in the current work, after estimating the personality of a teacher from the self-report as well as the learner's perspective, physiological signals-based prediction is also done. Additionally, to make the current work clearer and result-oriented, some hypothesis has been designed in terms of personality traits.

2.5 Extroversion

Teachers with extroversion traits like to involve themselves in social interaction and enjoy more face-to-face interactions as it acts as a positive stimulus for them. They are more friendly and always enjoy to involve in conversations (Arya et al., 2022). In contrast, introverted people are found to be more comfortable with the online environment as they are not much comfortable with collaborative tasks and feel hesitant (Voorn & Kommers, 2013).

Hypothesis 1. The extroversion trait is negatively correlated with the liking of Online teaching.

2.6 Agreeableness and Conscientiousness

Agreeableness is a trait that describes a person as kind, friendly and helpful. They give value to other people and are also concerned about their well-being. High levels of agreeableness show the teacher will always be positive about the OT and ready to help learners in any scenario (Rivers, 2021). Similarly, the high levels of conscientiousness talk about the punctuality or sincerity of a teacher. They adapt OT scenarios very responsibly and are dedicated to their duty. On the contrary, low levels of conscientiousness reflect the casualty of a teacher (Bhagat et al., 2019).

Table 2 Physiological signals based personality prediction

Citation	Modalities	Filter	Features	Model	Results
Wache, 2014	ECG, EDA, and EEG	bandpass filter 4- 45 Hz (EEG), low-pass filter cut-off at 60 Hz (ECG & EDA)	low-level descriptors and statistical features	SCA-GCN	Using binary classification, the accuracy of 72.1%, 69.5%, and is achieved for the dimensions of Openness and Emotion Stability
Miranda-Correa et al., 2021	EEG, ECG, GSR, and Face Videos	high-pass filter with a cut-off frequency at 2 Hz, blind source separation (EEG), low-pass filter with 0.2 Hz and 0.08 Hz cut-off frequencies (GSR)	time domain, frequency domain, and time–frequency features	SVM, Gaussian NB	Among EEG, ECG, and GSR, the best modality considered for the prediction of all personality traits is EEG GSR + ECG also gives good results for Extraversion, Agreeable, and Openness prediction
Zhao et al., 2018	EEG and subjective ratings	bandpass frequency filter 1–45 Hz	statistical and frequency domain feature	SVM	During elicitation of positive videos, Extraversion—81.08%, Agreeableness—86.11%, and Conscientiousness—80.56% classification results got improved While for negative ones, Neuroticism accuracy ranges between 78.38–81.08% showing good results

Table 2 (continued)

Citation	Modalities	Filter	Features	Model	Results
Subramanian et al., 2018	EEG, ECG, GSR, and facial activity	filtration using the Matlab toolbox	statistical and frequency domain features	NB, SVM (linear), SVM-RBF	ECG features give the best personality traits prediction performance followed by EEG, GSR, and facial landmarks. Agreeableness, Emotional stability, and conscientiousness are accurately predicted by ECG. EEG features are found to be ideal for recognizing Extraversion. Facial and GSR modalities work well for the Openness trait
Abadi et al., 2015	EEG, ECG, GSR, and facial landmarks	adaptive bandpass filter, low pass filter	time domain, and frequency domain feature	Linear Regression	ECG + GSR signals achieve a 70% + 8% F1 score on the extraversion trait EEG signals achieve a 69% + 6% F1 score on the Openness trait
Miranda-Correa & Patras, 2018	EEG	high-pass filter with a 2 Hz cut-off frequency	Time and frequency domain features	CNN and RNN	This multi-task cascaded deep learning network performs better for predicting personality traits corresponding to various video stimuli

SCA-GCN Siamese content-attentive graph convolutional network; *CNN* Convolutional neural network; *RNN* Recurrent neural network; *NB* Naïve bayes

Hypothesis 2. The agreeableness trait is positively correlated with the liking of Online teaching.
Hypothesis 3. The conscientiousness trait is positively correlated with the liking of Online teaching.

2.7 Neuroticism and Openness

Neuroticism trait is more related to the emotional values of an individual. High levels of neuroticism reflect the emotional instability of teachers i.e. they tend to have uncertainty in their mind that generally lead to various issues like anxiety, and depression. In other words, low levels neurotic teachers were found more comfortable with OT scenarios (Watjatrakul, 2020). The other important personality trait is Openness in which teachers are more willing to explore new ideas and things. They are not conserved and always have a positive attitude toward learning online technologies. Teachers having low levels of openness don't accept change very easily (Göncz, 2017).

Hypothesis 4. There is a negative correlation between neuroticism trait and liking for Online teaching.
Hypothesis 5. There is a positive correlation between openness trait and liking for Online teaching.

3 Experimental methodology

This section proposes a framework that is designed for investigating the teacher's personality as shown in Fig. 1. A mixed approach is used to identify the personality types from the self-reported data as well as physiological responses. With this, the learner also shares his perspective of the teacher's personality which reflects its relation with the liking of OT. Firstly, the information about the subjects chosen for the experiment is presented. Following that, the approaches are explained clearly in the next sections.

3.1 Subjects

For the current analysis, 14 university teachers (9 Females, 5 Males) aged between 30 to 45, were chosen for the experiment. These teachers were very well aware of OT methods and conducted online synchronous classes. With this, 18 graduation learners (11 Males, 7 Females) aged between 18–24 years were nominated from the class of selected teachers. They were supposed to attend a minimum of 15 lectures with full participation so that they can provide genuine

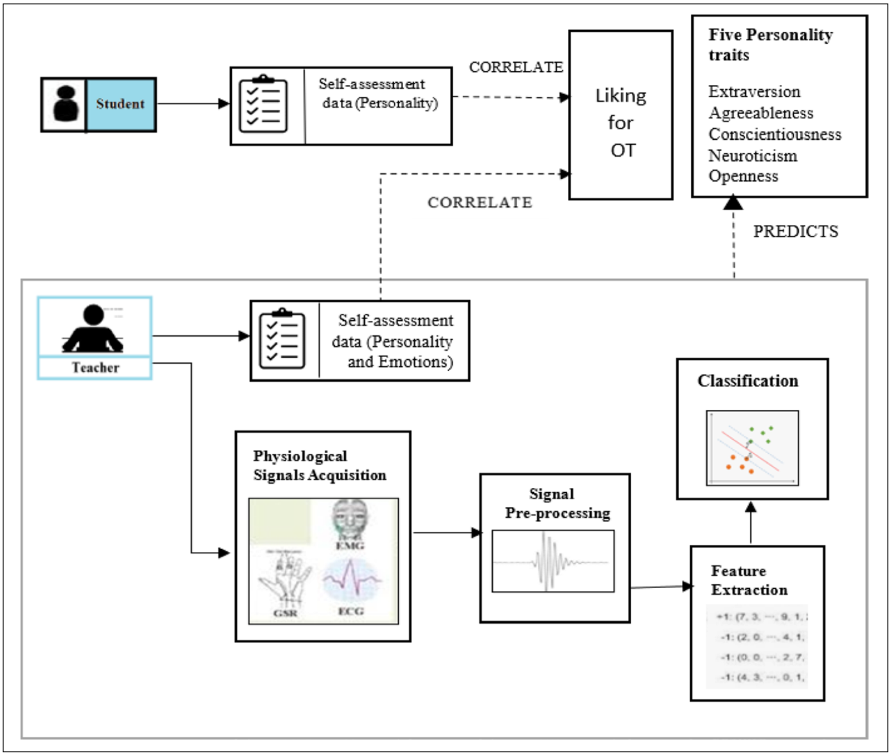

Fig. 1 The proposed framework for personality prediction

feedback. It has also been assured that they understand English very well and have knowledge of using online technology.

4 Investigating a teacher's personality from a learner's perspective

In this approach, learners report about teachers' personality traits and share their perspectives that whether teachers like teaching online or not. As explained earlier, the Big Five-factor questionnaire is used to measure personality, therefore, learners fill out this form along with the liking factor also. The procedure to conduct this analysis is also discussed.

4.1 Procedure

The questionnaire was shared online with learners in which for each personality dimension further 10 sub-traits were given along with their meaning. Learners rate all those traits using a 7-point Likert scale (Miranda-Correa et al., 2021). After this, the average value from all those sub-traits was calculated and it became the final value of that personality trait. For instance, in Extraversion, the further ten traits mentioned in the Big Five Factor questionnaire are Open, Warm-hearted, Extroverted, Exuberant, Vivacious, inward-looking Introvert, Reserved, Silent, and Shy. Learners rate these traits out of 7 and the average of all these will be the final value of the Extraversion trait. In the same way, other dimensions Agreeableness, Neuroticism, Conscientiousness, and Openness also have further 10 traits and from them, the final median value is calculated. Along with this, these learners have also shared their views regarding the teacher's liking for OT scenarios in terms of 0 and 1. 0 is for No, and 1 for Yes.

4.2 Data summary

Out of 18 learners, few learners have not reported their perception of teacher personality traits. Table 3 is representing the data about how many learners have given their feedback. For 18 learners, lear_1 to lear_18 and for 10 teachers, educ_1 to educ_10 terminology is used. In Table 3, 'Y' is used for those learners who have filled in the data and 'N' for those who have not submitted any feedback to teachers.

4.3 Results

This section shows the strength of the relationship between personality traits and the teacher's liking for OT scenarios from the learner's perspective. To evaluate this, correlation analysis, an approach to discover the dependencies or relation between any two variables is used (Prematunga, 2012). The Pearson correlation coefficient is calculated between personality and liking which gives the value that generally lies between -1 to + 1 and Zero (0) implying no correlation. Positive correlations imply that an increase in one variable increases in another one also. If the value is 1, there is a perfect positive relationship between the two variables. Negative correlations imply that as one value increases, the other will decreases. So, the following table shows Pearson's correlation between personality traits and teachers' liking for OT scenarios from the learner's point of view.

4.4 Analysis

Table 4 shows the relationship between all the personality traits and the teachers liking for OT from learners' perspectives.

Firstly, in between personality traits, it has been observed that there is a highly significant correlation between Extraversion (Ext) and Openness (Open) traits. It means a teacher who is an extrovert would also love to be open, ambitious, and ready for new experiences. Similarly, Agreeable (Agr) and Conscientiousness (Conc) have a significant correlation between them. Neuroticism (Neu) is also positively correlated with all personality traits.

Along with this, a correlation between personality traits and liking has also been analyzed and results are shown in Table 4. These results reveal that a teacher with

Table 3 Learners reported personality traits of teachers

Teachers/learners	educ_1		educ_2		educ_3		educ_4		educ_5		educ_6		educ_7		educ_8		educ_9		educ_10	
	Per	lik	Per	lik	Per	lik	Per	lik	Per	lik	Per	Lik	Per	lik	Per	lik	Per	lik	Per	lik
lear_1	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
lear_2	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_3	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_4	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_5	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	N	N	Y	Y
lear_6	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_7	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_8	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y
lear_9	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_10	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_11	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N
lear_12	Y	Y	N	N	Y	Y	Y	Y	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y
lear_13	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_14	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_15	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_16	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_17	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
lear_18	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Reports	15		16		18		17		17		16		17		18		17		16	

Table 4 Pearson's correlation between personality dimensions and liking factor

Traits	Ext	Agr	Conc	Neu	Open	Liking
Ext	1.000	-0.045	0.045	0.352	0.685*	-0.056
Agr		1.000	0.478*	0.282	-0.367	0.233
Conc			1.000	0.045	0.156	0.234
Neu				1.000	0.258	-0.123
Open					1.000	0.324*

* shows a strong positive correlation

high levels of Agr, Conc, and Open is more liking the OT as they have a positive correlation between them. On the contrary, teachers that are extrovert and neurotic are not liking OT much as there is a negative correlation between Ext, Neu, and Liking. These results also satisfy the hypothesis that has been assumed earlier.

H1- The extroversion trait is negatively correlated with the liking of Online teaching (Accepted).

There is a negative correlation between Extraversion and Liking factor which satisfies the hypothesis also. It is because extrovert teachers love to have more face-to-face interactions as compared to online.

H2- The agreeableness trait is positively correlated with the liking of Online teaching (Accepted).

There is a positive correlation between Agreeableness and the Liking factor. This satisfies the hypothesis that learners that are cooperative and concerned for others are liking the OT scenario.

H3- The conscientiousness trait is positively correlated with the liking of Online teaching (Accepted).

From the results, it is clear that people with high levels of Conscientiousness are comfortable with OT scenarios. Hence, the hypothesis is justified.

H4- There is a negative correlation between neuroticism traits and liking for Online teaching (Accepted).

Teachers that are highly neurotic, unable to accept the OT scenario as they are more emotionally unstable or become anxious. Therefore, the results satisfy this hypothesis also.

H5- There is a positive correlation between openness traits and liking for Online Teaching (Accepted).

Teachers who are open to new experiences, also eager to use OT tools and technologies. They accept changes positively and therefore, justify their positive relation with liking for the OT.

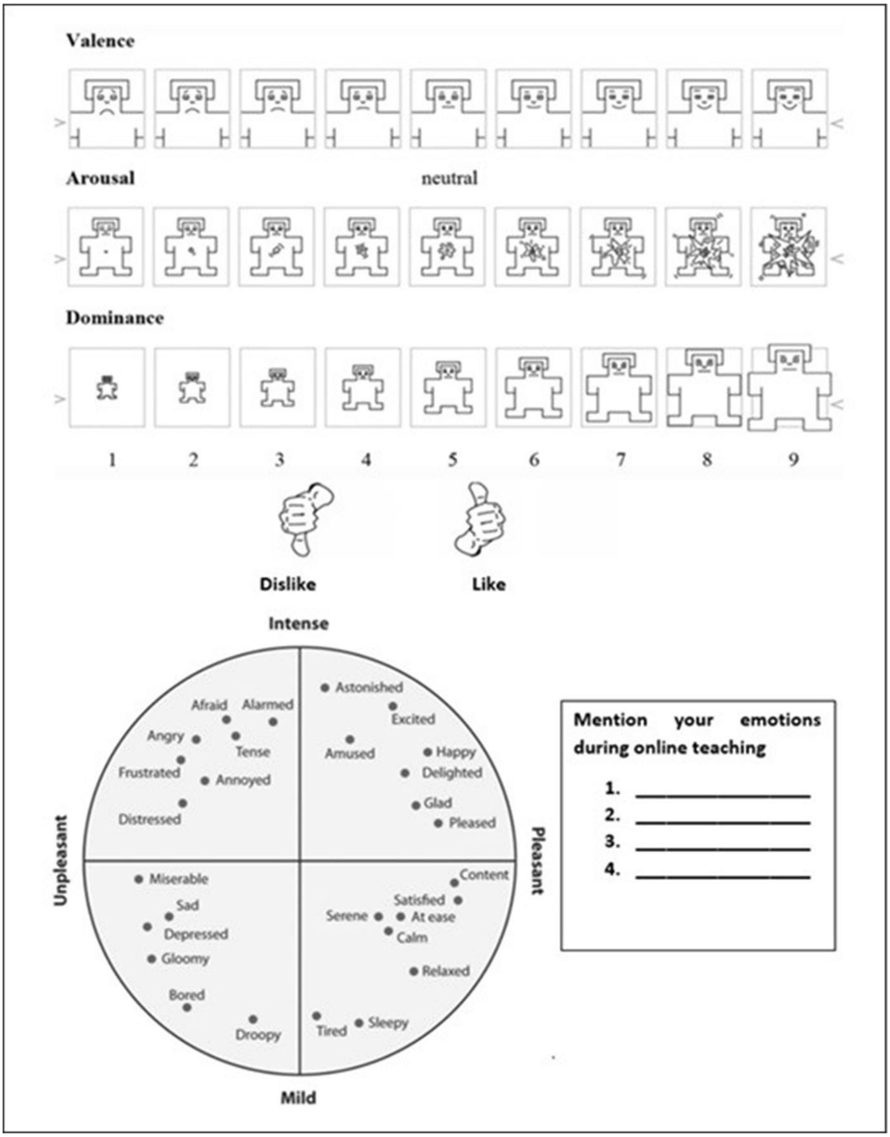

Fig. 2 Self-assessment form filled by the subject

5 Investigating a teacher's personality from their perspective in combination with their emotions for OT

In this approach, teachers were asked to fill out two forms related to their personality and emotions towards OT. First, a Big five-factor personality online form was shared among the teachers and they report their personality traits using 7 points Likert scale. Along with this, one more emotion-related Self-assessment Manikins (SAM) form as shown in Fig. 2 was also filled out by teachers to judge their perception of OT.

This form evaluates the emotions of a teacher by compiling Valence, Arousal, and Dominance (Subramanian et al., 2018). Valence describes the nature of emotion whether it is a positive one or a negative one. Arousal reflects the power of emotion which means how intensely a person is feeling that particular emotion (Arya et al., 2021). The third dimension is dominance which tells about the strength of an emotion. In other words, it explains the degree of control generated by emotion that a person is feeling like dominating the emotion (Bălan et al., 2020).

For measuring these dimensions, a 9-point scale was used in which for Valence, 1 was considered very negative to 9—very positive. Same for Arousal, 1 point is—very boring to 9 points is very exciting. For dominance, 1 point is- controlling the emotion, and 9 points—in control of emotion are described. Along with this, the liking factor concerning online teaching was also mentioned where subjects select any one option from two- I like it (1) or I don't like it (0). In the end, for more understanding of the feelings, some of the most felt emotions were also reported by the subjects shown in the circumplex model of affect.

5.1 Results

5.1.1 Emotion analysis

Teachers have reported their emotions towards OT using the SAM form. Emotions are measured in three dimensions i.e. valence (Val), arousal (Aro), and dominance (Dom). With this, they have told about the liking factor and mentioned some emotions using the Circumplex model of Affect also. To understand the relationship between the emotions of teachers and their liking for OT scenarios, Pearson's correlation method is used to find and their results are shown in Table 5.

This table shows that valence and liking are highly correlated which means teachers with high levels of valence (positive feeling) also like the scenario of OT. On the contrary, low levels of valence are more concerned with the disliking of OT. Similarly, arousal is having negative correlation with liking. has a significant correlation with dominance. The more aroused (excited) the person is, the more he gets

Table 5 Pearson's correlation between emotion dimensions

	Val	Aro	Dom	Liking
Val	1	-0.105	-0.173	0.635**
Aro		1	0.546*	-0.294
Dom			1	-0.089
Liking				1

** and * shows a significant correlation controlled by emotions. In contrast, less arousal (calm) subjects have more control over their emotions.

5.1.2 Personality analysis

Teachers have used 7 points Likert scale to assess personality traits. After collecting the data from all teachers the mean value is calculated for each personality trait. For example, Ext is 4.74, Agr-4.02, Con—3.58, Neu—4.01, and Open-4.33. Figure 3 shows the distribution of the personality scores dully filled by the teachers by highlighting their mean value line in the box plot.

Further, with the help of Spearman's Rank correlation coefficient, strength between five personality dimensions and liking for OT has been measured as shown in Table 6. It can be judged from the table that there is a significant, moderate, and positive correlation between Agr, Conc, and Open with the liking factor or OT. It also shows that the Ext and Neu are negatively correlated with liking. In other words, teachers also report that with high levels of extraversion and neuroticism, teaching in OT scenarios is not much interesting.

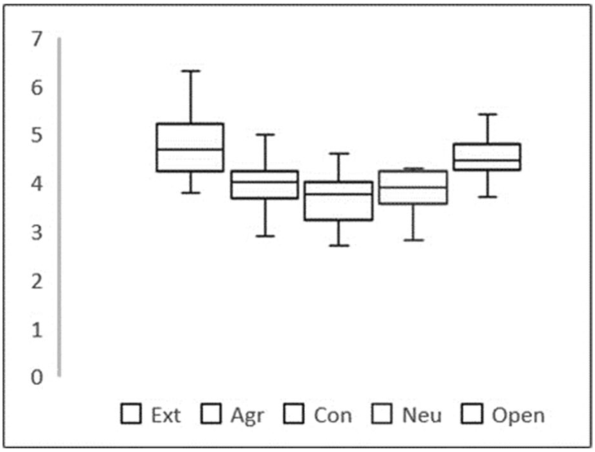

Fig. 3 Box plot showing the distribution of five personality traits

Table 6 Pearsons's correlation between Big five personality traits and liking

Personality traits	Ext	Agr	Conc	Neu	Open	Liking
Ext	1	0.012	-0.080	0.258	472*	-0.080
Agr		1	0.233*	0.150	-0.288	0.233
Conc			1	0.045	0.258	0.352*
Neu				1	0.156	-0.382*
Open					1	0.258*
Liking						1

*shows a significant correlation

5.2 Findings

Investigating teachers' personalities from the learners as well as their perspectives has given a lot of information about their feelings about OT. The results showed what kind of personality of teachers is being liked by the learners in the OT scenario which could make the teaching–learning process more effective. Second, It also showed what kind of personality of teachers like Online education scenarios or what are their feelings about OT.

However, the analysis done for the personality of a teacher is completely questionnaire-based. Learners and teachers self-report their feelings which could be biased. As people, percept and rate differently for the same as well as different emotions, the self-assessment-based results can be biased. Therefore, to investigate a teacher's personality more accurately, despite the questionnaire, the physiological responses like ECG, EMG, and GSR of a teacher were also recorded. As physiological parameters are uncontrollable factors and considered a good factor for personality prediction, so the third approach is proposing a framework to ensure that a teacher's personality could be investigated using physiological responses and that is why they play an important part.

6 A personality prediction framework based on physiological signals and emotive responses

As mentioned earlier, along with self-reported data, the physiological parameters were also analyzed to judge the personality of a teacher. The whole process of personality prediction using physiological signals is explained below.

6.1 Experimental setup

To conduct the study, a total of 10 teachers (Female: 6, Male: 4) were considered as subjects same as for questionnaire-based analysis. They were pre-informed regarding the experiment and asked to fill out the consent form that confirm they are ready for the experiment. The naming conventions used for all 10 teachers were from educ_1 to educ_10. All of them were having normal vision, right-handed with no physical or mental ailment. The whole setup was arranged in a room where the subject had to report 30 min before the lecture. The setup included one laptop (14-inch LCD screen, resolution-1920 × 1080), installed zoom software, and some additional tools that were required for online teaching. A comfortable sitting and proper daylight arrangement were done in the room. Along with this, three bio-sensors ECG—AD8232 ECG monitor, EMG, and GSR- Grove Sensor from Seed Studio circuits along with Battery and Aurdino chip were also installed to fetch physiological signals. They were also instructed to have very few moments during the experiment to get noise-free signals.

Fig. 4 Subject taking an online class by wearing three sensors: ECG (wrist), GSR (fingers), and fEMG (eyebrows)

6.2 Subject preparation

After taking consent, the subject has been prepared for the experiment. The three biosensors ECG, facial EMG, and GSR were attached to the subjects as per the standards as shown in Fig. 4. The GSR Grove sensor includes two finger band electrodes that were fixed to the index and middle finger phalanges of the left hand to measure the skin conductance. The second is ECG in which two electrodes were positioned on the wrist of both arms, and the reference electrode was there on the right leg bone to fetch the cardio activity signals. For recording facial activity signals, fEMG sensor including two electrodes was placed on the corrugator supercilii muscles, and ground on the forehead as per the standards. After applying all the sensors, physiological signals were fetched.

6.3 Experimental protocol

This section put light on the procedure followed for experimenting. As per the instructions, each subject was asked to report for the experiment 20 min before their online class. Further, the respective body parts were cleaned with the gel, and fEMG, ECG, and GSR were applied to them. After this, before starting the session, a mock experiment was just conducted for 2 min to ensure that all the equipment was working properly or not. Then, the session started and parallelly physiological signals were fetched for 20 min duration. Only theory lectures were considered for the experiment as practical sessions need a lot of hand movements like typing code, drawing figures, etc. which leads to the generation of super noisy signals.

This experiment has been conducted on each teacher in continuation for 5 days taking the same class. During each session, physiological signals were captured and after that, the subject has to fill out the emotion questionnaire again in terms of valence and arousal also. For the experiment, the subject has to fill out the emotion

Table 7 Total no. of recordings recorded and analyzed for the experiment

Subject	Day_1			Day_2			Day_3			Day_4			Day_5			Total Recordings considered (subject-wise)		
	ECG	fEMG	GSR	ECG	fEMG	GSR	ECG	fEMG	GSR	ECG	fEMG	GSR	ECG	fEMG	GSR	ECG	fEMG	GSR
educ_1	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	×	✓	✓	✓	4	5	4
educ_2	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	4	5
educ_3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	5	5
educ_4	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	4	5
educ_5	×	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4	5	4
educ_6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	5	5
educ_7	✓	✓	✓	✓	✓	✓	×	✓	×	✓	✓	✓	✓	✓	✓	4	5	4
educ_8	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	5	5
educ_9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	5	5
educ_10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	5	5	5
Total Recordings considered for the final analysis																47 + 48 + 47 = 142		

questionnaire on the daily basis after the lecture. However, the personality questionnaire is asked to fill only once as it describes the long-term personality traits.

At last, the total recordings which were acquired after the whole experiment for each physiological signal were 50 (no. of subjects (10) * no. of days (5)). In total, 150 recordings of ECG, fEMG, and GSR were attained. Out of these, some of the recordings were not considered for the final analysis due to hardware failure or unnecessary artifacts present in the signals because of body movements. In Table 7, the 'tick' symbol represents the recording that is considered for the final analysis, and the 'x' symbol denotes the excluded one. For instance, in the case of teach_1, the ECG signal on day 4 got failed due to electricity issues/sensor problems. On the same day, the recording retrieved from GSR signals was also noisy due to hand movements. Therefore, in total 142 recordings were included in the final analysis.

6.3.1 Data acquisition

Once the experiment has been conducted, the values of ECG, GSR, and fEMG sensors have been recorded. GSR is used to measure the conductivity of the skin that is caused by the variation of the human body sweating. By positioning two electrodes

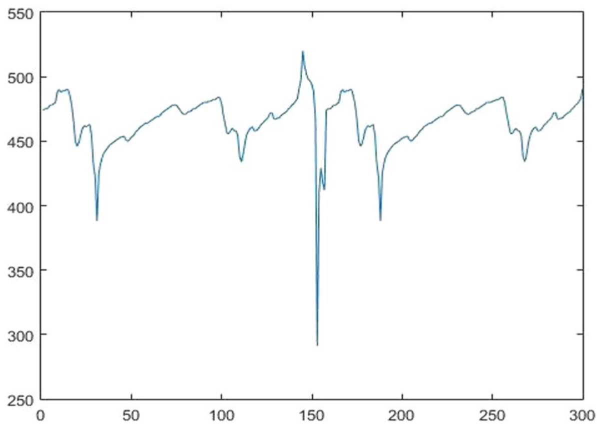

Fig. 5 Raw GSR signal

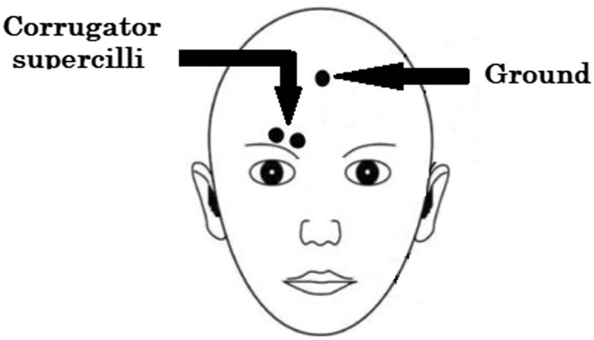

Fig. 6 Position displaying the electrode placement on the face

on the second and third finger, GSR in terms of voltage (power) is measured. It can be observed that the output voltage is relative to the skin conductance value (Seo et al., 2019). The more strained the person is, the more his hands will sweat, so his conductance will decrease. Implementing GSR is very easy and pocket-friendly for physiological research. It gives information about the intensity or arousal of emotion. In this experiment, during online teaching, skin conductance at the sampling rate of 2 Hz is calculated. The raw signal is shown in Fig. 5. After that, to fetch the important features this raw signal is processed or filtered with the help of a bandpass filter with a passband frequency of 0.5 Hz.

ECG is used to measure the heart activity of an individual. It helps widely in recognizing the emotions of a person (Bexton et al., 1986). For the current experiment, a pre-amplified electrocardiograph sensor connected with Ag/AgCI electrodes was used. An ECG signal was acquired at the sampling rate of 250 Hz. It is important to remain in a static position during ECG signal fetching. In our case, after giving prior instructions, a few teachers were still doing some movements like scrolling of mouse and hand motions. These movements created some noise and to remove this filtration process has been done. With this, parallelly **fEMG** is used to measure muscle activity that assists in investigating the feeling of an individual through facial muscles. For the current work, the corrugator supercilli muscle activity of a teacher was recorded during an online session (Murata et al., 2016). As it is shown in Fig. 6, two dots near the eyebrows record the muscle activity in terms of voltage, and one in the center is the ground is the proper spot for electrode placement. After fetching the raw signal at the rate of 2000 Hz, it was filtered and processed further for feature extraction.

6.3.2 Feature Extraction

Table 8 Time and frequency domain features

Modality	Features
GSR	mean, kurtosis, standard deviation, skewness, mean frequency, no. of local minima, Spectral power, SCR amplitude, and SCR peak count
fEMG	Mean frequency, median frequency, standard deviation, kurtosis, integrated EMG, EMG power spectrum, simple square integral, root mean square
ECG	Average heart rate, mean, median, standard deviation, kurtosis

The second phase following data acquisition is the feature extraction process. The features contain meaningful information about the signal. Multiple time and frequency domain features are there that reveal more about the feelings or personality of an individual. The features that have been considered for every signal are shown in Table 8. For GSR, time domain features- mean, standard deviation, kurtosis, skewness, no. of local minima, and frequency domain features like Spectral power, Skin Conductance Response (SCR) amplitude, and peak count were calculated.

Similarly, for fEMG and ECG, the mentioned features were extracted and put into the further step of Classification.

7 Classification and Results

In this section, the classification process for personality prediction is explained. The first finding shows the results of prediction using physiological signals only. The second one uses the combination of reported emotions with physiological signals put its features into the classifier and perform the personality prediction. Support Vector Machine (SVM) is used for classification purposes. Classification results are calculated in the form of an F1 score.

7.1 Finding 1: Personality prediction using physiological signals

For physiological signals-based personality prediction, 5 SVM classification models have been designed, and each model is responsible for the prediction of one particular personality trait. For classification, personality dimensions labels are divided into low and high classes by calculating the median value of each trait i.e. **Ext-4.5, Agr-4, Conc-3.7, Neu-3.9, Open-4.4**.

Further to assuring the accurate prediction or working of the classification model, threefold cross-validation scheme is applied as it enhances the effectiveness of the model and assists in producing less biased results. Thus, after applying this validation in the SVM model, F1-score is obtained for all the personality traits using all the physiological signals like GSR, ECG, and facial EMG individually as well as in combination which are displayed in Table 9.

From this table, it can be observed that for maximum personality dimensions facial EMG and GSR achieved better results. In other words, for Ext, Agr, and Open, GSR is the best modality. Similarly, facial EMG also gives a good score for Ext, Agr, and Conc as well. For Neu, ECG gives the highest f1 score. Therefore, from the table, it could be concluded that ECG is not the best modality among all of them. In addition to this, these modalities are combined in pairs to predict the five personality dimensions and their F1 score is also displayed. It is also observed from the table

Table 9 F1- score (for high and low class) over each personality trait based on physiological modality

Signals	Ext	Agr	Conc	Neu	Open
GSR	0.545	0.810**	0.285	0.207	0.510**
ECG	0.428	0.632	0.470	0.475**	0.400
Facial EMG	0.615**	0.714	0.545**	0.400	0.285
ECG + facial EMG	0.527**	0.684	0.525**	0.369	0.400
ECG + GSR	0.545	0.800	0.461	0.414	0.400
facial EMG + GSR	0.400	0.875*	0.500	0.667**	0.333
GSR + ECG + facial EMG	0.543	0.763	0.541	0.666	0.314

** represents the highest f1-score for that personality trait corresponding to physiological modality

Table 10 F1-score for personality identification using signal + self-rating based results

Signal + self-rating	Ext	Agr	Conc	Neu	Open
GSR + V + A	0.666*	0.842*	0.500	0.736*	0.500*
ECG + V + A	0.533	0.782	0.470	0.600	0.400
Facial EMG + V + A	0.500	0.857*	0.651	0.769*	0.333

that in combination, GSR and facial EMG give good results for Agr and Neu personality traits. Also, ECG and facial EMG work well for Ext, Conc, and Open traits. At last, all three modalities are combined which gives average results but could not consider the best one.

7.2 Finding 2: Personality predictions using physiological signals and emotion responses

In this sub-section, along with physiological features, self-reported responses of emotions in terms of valence (V) and arousal (A) are also added as they also play an important part in the prediction of the personality of an individual. Table 10 shows the result, in which also five linear SVM models using a threefold cross-validation scheme have been designed. The purpose of this classification is to analyze how well the self-reported emotions of a subject along with physiological parameters could help in predicting their personality.

As can be seen from the results, the combination of self-rating that is reported by the teacher along with physiological signals also gives good results in personality prediction. GSR along with self-reported emotions gives good results for Ext, Agr, Neu, and Open traits prediction. But for Con trait, it gets decreased. Thus, after analysis, it could be observed that the results provided by the fusion of valence and Arousal with physiological signals can be taken into consideration in the future which may produce good output.

8 Conclusion

This work is an attempt to investigate the effect of a teacher's personality on the likelihood of online teaching from two perspectives. In the first, a learner shares his views on teachers' personalities and how much they like online teaching. Second, teachers self-report their personalities and also share their sentiments about online teaching. An analysis has been done from both perspectives and some interesting results have been acquired from the learner's perspective. These results reveal what kind of personality traits of teachers are more comfortable with the OT. In addition to this, physiological signals i.e. ECG, GSR, and fEMG individually as well as an infusion with emotive responses (valence and arousal) based personality prediction is also done as it plays an important role in effective online teaching. Self-reported personality data may produce biased results, which is why physiological responses are considered to ensure the authenticity of the analysis. The results from this analysis suggest that body parameters could be used as a meaningful reference by future researchers to make online teaching and learning more effective. It also shows that the combined physiological measures could also be considered for personality identification and can be applied in the future for various domains.

8.1 Limitations and future directions

The current work gives a new direction to those researchers who are working in the education domain, especially in making online teaching and learning scenarios more effective. Some limitations were also there which can be considered for improving results. The sample size of teachers and students was limited so it could be increased for critical analysis of the personality traits. Along with this, other than ECG, GSR and fEMG there are some other physiological responses like EEG, Skin temperature, and Blood volume pressure that could be analyzed for accurate results.

For the physiological signals-based analysis, some time and frequency domain features have been extracted, however, some more meaningful features could be explored that will help a lot in improving personality recognition results. With this, changes can be made to the placement of the ECG sensor from the arm and wrists to the trapezius muscles which leads to fewer body movements and give accurate results. Some other advanced filtration techniques in combination with various classification models could be used so that an effective approach could be discovered.

Acknowledgements The author extends gratitude to teachers and students who participated in the study.

Data availability The data collected and analyzed in the study are available from the corresponding author upon reasonable request.

Declarations

Conflicts of interests/Competing interests The authors declare no conflict of interests.

References

Abadi, M. K., Correa, J. A. M., Wache, J., Yang, H., Patras, I., & Sebe, N. (2015). Inference of personality traits and affect schedule by analysis of spontaneous reactions to affective videos. 1*1th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, (pp. 1–8). https://doi.org/10.1109/FG.2015.7163100

Almaiah, M. A., & Alyoussef, I. Y. (2019). Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of E-learning system. *Ieee Access, 7*, 171907–171922.

Arispe, K., & Blake, R. J. (2012). Individual factors and successful learning in a hybrid course. *System, 40*(4), 449–465. https://doi.org/10.1016/j.system.2012.10.013

Arya, R., Kumar, A., & Bhushan, M. (2021). Affect Recognition using Brain Signals: A Survey. In: V. Singh, V. K. Asari, S. Kumar, & R. B., Patel (Eds.), *Computational Methods and Data Engineering. Advances in Intelligent Systems and Computing* (vol 125)7. Springer, Singapore. https://doi.org/10.1007/978-981-15-7907-3_40

Arya, R., Kumar, A., Bhushan, M., & Samant, P. (2022). Big five personality traits prediction using brain signals. *International Journal of Fuzzy System Applications (IJFSA), 11*(2), 1–10. https://doi.org/10.4018/IJFSA.296596

Bălan, O., Moise, G., Petrescu, L., Moldoveanu, A., Leordeanu, M., & Moldoveanu, F. (2020). Emotion classification based on biophysical signals and machine learning techniques. *Symmetry*, *12*(1). https://doi.org/10.3390/sym12010021

Basu, A., Dasgupta, A., Thyagharajan, A., Routray, A., Guha, R., & Mitra, P. (2018). A portable personality recognizer based on affective state classification using spectral fusion of features. *IEEE Transactions on Affective Computing, 9*(3), 330–342.

Bexton, R. S., Vallin, H. O., & Camm, A. J. (1986). Diurnal variation of the QT interval—Influence of the autonomic nervous system. *British Heart Journal, 55*, 253–258. https://doi.org/10.1136/hrt.55.3.253

Bhagat, K. K., Wu, L. Y., & Chang, C. (2019). The impact of personality on students' perceptions towards online learning. *Australasian Journal of Educational Technology, 35*(4)*,* 98–108. https://doi.org/10.14742/ajet.4162

Borg, M. E., Butterfield, K. M., Wood, E., Zhang, H. H., & Pinto, S. (2021). Investigating the impacts of personality on the use and perceptions of online collaborative platforms in higher education. *SN Social Sciences*, *1*(40). https://doi.org/10.1007/s43545-020-00053-x

Bradley, M. M., & Lang, J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry, 25*(1), 49–59. https://doi.org/10.1016/0005-7916(94)90063-9

Butt, A. R., Arsalan, A., & Majid, M. (2020). Multimodal personality trait recognition using wearable sensors in response to public speaking. *IEEE Sensors Journal, 20*(12), 6532–6541. https://doi.org/10.1109/JSEN.2020.2976159

Donnellan, M. B., Oswald, F. L., Baird, B. M., & Lucas, R. E. (2006). The mini-IPIP scales: Tiny-yet effective measures of the Big Five factors of personality. *Psychological Assessment, 18*(2), 192–203. https://doi.org/10.1037/1040-3590.18.2.192

Evans, H. K. (2014). An experimental investigation of videotaped lectures in online courses. *TechTrends, 58*(3), 63–70.

Göncz, L. (2017). Teacher personality: A review of psychological research and guidelines for a more comprehensive theory in educational psychology. *Open Review of Educational Research, 4*(1), 75–95. https://doi.org/10.1080/23265507.2017.1339572

Grieve, R., Moffitt, R. L., & Padgett, C. R. (2019). Student perceptions of marker personality and intelligence: The effect of emoticons in online assignment feedback. *Learning and Individual Differences, 69*, 232–238. https://doi.org/10.1016/j.lindif.2018.02.008

Hasnul, M. A., Aziz, N. A. A., Alelyani, S., Mohana, M., & Aziz, A. A. (2021). Electrocardiogram-based emotion recognition systems and their applications in healthcare-a review. *Sensors (Basel)*, *21*(15). https://doi.org/10.3390/s21155015

Ismail, S., Basharirad, B., & Ismail, S. (2017). Significant of MBTI personality model on decision making in university program selection. *2nd International Conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE).*

Kaup, S., Jain, R., Shivalli, S., Pandey, S., & Kaup, S. (2020). Sustaining academics during covid-19 pandemic: The role of online teaching-learning. *Indian Journal of Ophthalmology, 68*(6), 1220–1221. https://doi.org/10.4103/ijo.IJO_1241_20

Maican, C. K., Cazan, A. M., Lixandroiu, R. C., & Dovleac, L. (2019). A study on academic staff personality and technology acceptance: The case of communication and collaboration applications. *Computers & Education, 128*, 113–131. https://doi.org/10.1016/j.compedu.2018.09.010

Martin, F., Budhrani, K., & Wang, C. (2019). Examining faculty perception of their readiness to teach online. *Online Learning Journal, 23*(3), 97–119. https://doi.org/10.24059/olj.v23i3.1555

Martin, F., Wang, C., & Sadaf, A. (2018). Student perception of helpfulness of facilitation strategies that enhance instructor presence, connectedness, engagement, and learning in online courses. *The Internet and Higher Education, 37*, 52–65. https://doi.org/10.1016/j.iheduc.2018.01.003

McCrae, R. R., & Costa, P. T. (2004). A contemplated revision of the NEO Five-Factor Inventory. *Personality and Individual Differences, 36*(3), 587–596.

Miranda-Correa, J. A., & Patras, I. (2018). A Multi-Task Cascaded Network for Prediction of Affect, Personality, Mood and Social Context Using EEG Signals. 1*3th IEEE International Conference on Automatic Face & Gesture Recognition. (*pp. 373–380). https://doi.org/10.1109/FG.2018.00060

Miranda-Correa, J. A., Abadi, M. K., Sebe, N., & Patras, I. (2021). AMIGOS: A dataset for affect, personality and mood research on individuals and groups. *IEEE Transactions on Affective Computing, 12*(2), 479–493. https://doi.org/10.1109/TAFFC.2018.2884461

Mishra, L., Gupta, T., & Shree, A., (2020). Online teaching-learning in higher education during lockdown period of COVID-19 pandemic. *International Journal of Educational Research Open*. 1. https://doi.org/10.1016/j.ijedro.2020.100012

Mukhtar, K., Javed, K., Arooj, M., & Sethi, A. (2020). Advantages, limitations and recommendations for online learning during COVID-19 pandemic era. *Pakistan Journal of Medical Sciences, 36*(4), S27–S31. https://doi.org/10.12669/pjms.36.COVID19-S4.2785

Murata, A., Saito, H., Schug, J., Ogawa, K., & Kameda, T. (2016) Spontaneous facial mimicry is enhanced by the goal of inferring emotional states: Evidence for moderation of "Automatic" mimicry by higher cognitive processes. *PLoS ONE, 11*(4). https://doi.org/10.1371/journal.pone.0153128

Muthuprasad, T., Aiswarya, S., Aditya, K. S., & Jha, Girish K. (2021). Students' perception and preference for online education in India during COVID -19 pandemic. *Social Sciences & Humanities Open, 3*(1). https://doi.org/10.1016/j.ssaho.2020.100101

Noreen, S., Ali, A., & Munawar, U. (2019). The impact of teachers' personality on students' academic achievement in Pakistan. *Global Regional Review, IV*, 92–102.

Prematunga, R. K. (2012). Correlational analysis. *Australian Critical Care, 25*(3), 195–199. https://doi.org/10.1016/j.aucc.2012.02.003

Pushpa Latha, G. C., Hema, C. R., & Paulraji, M. P. (2013). Neural network based classification of human emotions using Electromyogram signals. *International Conference on Advanced Computing and Communication Systems*. (pp. 1–4). https://doi.org/10.1109/ICACCS.2013.6938762

Rivers, D. J. (2021). The role of personality traits and online academic self-efficacy in acceptance, actual use and achievement in Moodle. *Education and Information Technologies, 26*, 4353–4378. https://doi.org/10.1007/s10639-021-10478-3

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F., (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? *Computers in Human Behavior*, *118*. https://doi.org/10.1016/j.chb.2020.106675

Seo, J., Laine, T. H., & Sohn, K.-A. (2019). An Exploration of Machine Learning Methods for Robust Boredom Classification Using EEG and GSR Data. *Sensors*, *19*. https://doi.org/10.3390/s19204561

Setiana, D., Kusumaningrum, B., & Purwoko, R. (2021). The students' interest in online learning in higher education during the Covid-19 pandemic. *Edumatika Jurnal Riset Pendidikan Matematika, 4*. https://doi.org/10.32939/ejrpm.v4i2.932

Starr-Glass, D. (2013). From connectivity to connected learners: Transactional distance and social presence. Increasing student engagement and retention in e-learning environments: Web 2.0 and blended learning technologies. Bingley: Emerald Publishing. https://doi.org/10.1108/S2044-9968(2013)000006G007

Subramanian, R., Wache, J., Abadi, M. K., Vieriu, R. L., Winkler, S., & Sebe, N. (2018). ASCERTAIN: Emotion and personality recognition using commercial sensors. *IEEE Transactions on Affective Computing, 9*(2), 147–160. https://doi.org/10.1109/TAFFC.2016.2625250

Svendsen, G. B., Johnsen, J.-A.K., Almas-Sorensen, L., & Vitterso, J. (2011). Personality and technology acceptance: The influence of personality factors on the core constructs of the Technology Acceptance Model. *Behaviour & Information Technology, 32*(4), 323–334. https://doi.org/10.1080/0144929X.2011.553740

Voorn, R. J., & Kommers, P. A. (2013). Social media and higher education: Introversion and collaborative learning from the student's perspective. *International Journal of Social Media and Interactive Learning Environments, 1*(1), 59–73. https://doi.org/10.1504/IJSMILE.2013.051650

Wache, J. (2014). The Secret Language of Our Body: Affect and Personality Recognition Using Physiological Signals. In *Proceedings of the 16th International Conference on Multimodal Interaction (ICMI '14).* Association for Computing Machinery. (pp. 389–393). New York. https://doi.org/10.1145/2663204.2666290

Watjatrakul, B. (2020). Intention to adopt online learning The effects of perceived value and moderating roles of personality traits. *International Journal of Information and Learning Technology, 37*(1/2), 46–65. https://doi.org/10.1108/IJILT-03-2019-0040

Yu, D., & Shouqian, S. (2020). A systematic exploration of deep neural networks for EDA-based emotion recognition. *Information*, *11*(4). https://doi.org/10.3390/info11040212

Yu, Z. (2021). The effects of gender, educational level, and personality on online learning outcomes during the COVID-19 pandemic. *International Journal of Educational Technology in Higher Education, 18*(14). https://doi.org/10.1186/s41239-021-00252-3

Zhao, G., Ge, Y., Shen, B., Wei, X., & Wang, H. (2018). Emotion analysis for personality inference from EEG signals. *IEEE Transactions on Affective Computing, 9*(3), 362–371. https://doi.org/10.1109/TAFFC.2017.2786207